Social Agents
Agent-Based Modelling of Integrated Internal and Social Dynamics of Cognitive and Affective Processes
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Social Agents
Agent-Based Modelling of Integrated Internal and Social Dynamics of Cognitive and Affective Processes
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For Mum and Dad
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To learn, read
To know, write
To master, teach

~Hindu Proverb~

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Natalie van der Wal, March 12, 2012
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Part I: Introduction

Abstract. The main research question within this thesis is introduced: *how can an intelligent agent-based system be designed, that gives support to teams, based on their social interactions and internal processes?* The contribution of this thesis is the provision and extension of knowledge on how to analyse and design new, innovative computational models for human processes integrating social and individual internal functioning and involving both cognitive and affective elements. This research is innovative, in that it models and validates agent-based models that integrate internal and social dynamics plus affective and cognitive aspects. Usually, computational models do not focus on integrating all of these four aspects. The multiple research objectives are explained, as well as the methodology used to analyse, design and evaluate the agent-based models in this book. Moreover, the contents of each of the six parts of this thesis are outlined.
Chapter 1: Introduction

Imagine yourself standing on Dam Square, Amsterdam, on the 4th of May 2010 at 20:00 hours specifically. You find yourself in a large crowd of 20,000 people, all remembering people that have died in WWII and other military conflicts. [1] There is a national ceremony taking place, where the Dutch Royals, members of the cabinet and military leaders place wreaths on the monument, poems are read and the national anthem is played. The ceremony starts at 20:00 hrs, when the whole country is silent for 2 minutes, including all the people around you, standing on Dam Square, see Figure 1.1. Towards the end of the two-minute silence, suddenly, you can hear a loud scream coming from somebody at the square. Immediately it is chaos: a stampede of panicked people running away from the center of the square, falling crowd control barriers sounding like gunshots: WHAT DO YOU DO?

![Figure 1.1 The 20,000 people crowd on Dam Square, May 4th 2010, 20:00 hrs](image)

Your actions will depend on many factors. Do you run in the same direction as that of the majority of the people around you? Or perhaps you run against this direction to first grab your child or to go towards the location where you came from? Your emotions can be the result of mass emotion contagion: does the panic get to you too, or can you somehow stay calm? And what effect do your intentions and beliefs have on your emotions and vice versa? Do you believe that there is a terrorist on the square with a bomb so
that you are extra sensitive for information about escape routes? Or did you see that the person yelling was not a terrorist, but a confused person and do you try to stay on your spot in the hope the ceremony will continue. Do you try to calm down the people around you?

In this example one can see that crowd behaviour is a result of not only social processes (e.g., mass fear contagion), but also an individual’s internal processes (like emotion regulation, individual’s intentions and beliefs, or the internal interaction between cognitive and affective processes). Crowd behaviour can be investigated with computational models. Computational modelling is a research area in which researchers of different disciplines, like biology, neuroscience, bioinformatics and artificial intelligence, make computational models that can simulate real world processes, like neurons firing in the brain or a crowd running away from the center of a square. The computational models give insight into the real world phenomena that it models; it helps the researcher to understand the real world process better and to make predictions. Research in computational modelling tends to either focus on the individual, internal processes, e.g. [13] or on the social interaction processes, thereby abstracting from the internal processes, e.g. [3] [14]. The current research is innovative, in that it integrates social interaction processes with internal processes. It focuses on the dynamics of internal and social processes, like emotion regulation and emotion contagion, in different types of social relations. These internal and social processes have an important role not only in crowds, but also in families, groups and teams of colleagues or sportsmen. For example, the negative mood of a depressed spouse can affect the mood and stress buffer of the husband or wife (the informal caregiver), but will also affect the mood of the informal caregiver’s relations. Through internal processes of the informal caregiver, like coping, emotion regulation and social processes (like asking for help and receiving positive mood from others), he/she tries to stay healthy and in a positive mood. Furthermore, the group emotion and development level of a team that has to solve a problem or close an important international deal, for instance, also affects the group performance. A positive emotion is beneficial to the group performance and different group development levels require different leadership styles to result in an effective group performance.

Besides focussing on integrating social interactions and internal processes, this research also integrates cognitive and affective processes. These processes are not commonly modelled all together in the field of computational modelling, e.g. [13] aims at modelling cognitive processes and [11, 12] and [10] aim at modelling affective processes, but will be integrated in the current research. For example, emotion regulation (which involves cognitive processes) has an influence on emotion contagion (affective process).
A negative mood can spread through social interactions, with the speed and intensity depending on the personalities of the individuals involved and the intensities of their interactions. Moreover, within a specific person, mental states like beliefs and intentions can have influence on emotions, and vice versa. For example, when you are in an evacuation scenario and have a high fear level, it can bias your openness for information. You will likely become more sensitive for information about escape routes, than for non-survival information; like that the toilets are out of order on the station. The other way around, a lot of non-positive information about the world around you (e.g. the front of the train has been exploded, no exits on that side) can increase your level of fear. Also, your own emotions can affect valuation of your own intentions. For example, according to Damasio’s somatic marker hypothesis, every decision you make is influenced by your emotions towards each option. 

1.1 Motivation

The motivation for this research is to model and validate support agents for groups, based on computational models for social interactions and internal dynamics. Support agents, are artificial computer programs built into devices that can sense the behaviour of humans and reason about it, in order to support the human. This research will extend current research in which support for teams is only based on the social interactions, for example, communication network analysis, but not on individual (internal) processes, like, for example, emotion regulation; e.g. [16] [15]. [8].

The problem in creating agent-based support systems for teams lies in sensing, reasoning about and supporting the complex dynamics of a team. For example, crowd behaviour is the complex interaction between individual, internal processes (like belief and intention generation, emotion regulation, individual decision making) and social interactions (like mood and intention contagion, communications, walking patterns, group decision making, etc.). Agent-based models are required that can model social interactions between agents, the internal processes of each agent and all the relations between and amongst them.

In this book, it is assumed that this is done best by using agent-based models. This assumption stems from the recent development of the field of Ambient Intelligence, which is growing at a fast rate. Ambient Intelligence refers to electronic environments that are sensitive and responsive to the presence of humans. [2]. Its ultimate goal is to improve the quality of our life by a quiet, reliable and secure interaction with our social and material environment. In order to accomplish this, devices in the environment must process knowledge about humans and their functioning to show human-like
understanding [17]. This field seems to be the future for research and applications of personalised care and team support. Furthermore, agent-based models are used when it is important for the model to include individuals and what they do. Moreover, a specific approach to agent-based models is chosen. The agent models in this book are based on dynamic system models [13]. Dynamic system models are able to explain and model real-time processes that result in adaptive behaviour.

Teams or groups of people that can benefit from agent-based support systems are many, for example: informal caregivers of a person with a depression, persons responsible for crisis management, members of a space mission team, a sports team, teams that are in a board meeting, teams that have to solve problems, teams that perform high demanding or stressful tasks, such as air traffic controllers, law enforcers in an evacuation or riot scenario. They benefit from agent-based support, in the sense that the team performance improves, for example: more people survive an evacuation, riots don’t escalate, faster or more creative problem solving is achieved, and caregivers stay healthy and keep a positive mood.

The agent-based models in this book are innovative in different ways. The integration of social interactions and internal processes is innovative, as well as the integration of affective and cognitive processes. Furthermore, the models proposed in this book explore new domains; for example: computational models for the social support of informal caregivers and the support of group development and group emotion are proposed. Very few computational models exist in these areas yet. Moreover, some of the models introduced in this thesis, their underlying theories and the emotion recognition system proposed in Chapter 4, are validated by controlled experiments, which not only validate the models itself, but also contributes to research of similar computational models by investigating which model performs best.

The general approach towards building agent-based support models for teams is: first, agent-based models of the processes of a specific domain are explored. Next, ways are found to model interactions between internal processes and social interactions, plus affective and cognitive processes. Then, the models are evaluated by simulations, experiments and automatic property checking.

The strength of the current approach is that the models will be generic: they can be applied to different domains relatively easy and are easy to implement in any computer language. The limitation of every agent-based model is that a model is always a simplification of the real world. Choices have to be made which aspects of the real world phenomenon will be modelled and which not. A related limitation is that one always have to make modelling
assumptions, like that emotion can be modelled as a number in the interval [0, 1].

1.2 Research objectives

The main research question within this thesis is: \textit{how can an intelligent agent-based system be designed, that gives support to teams, based on their social interactions and internal processes?} The main question is very general and broad, it does not state in which domain or to what kind of team it can give support. This is, because in this book, many different domains are explored, like: the support of informal caregivers, group development, group emotion, crisis management and group evacuation. The general approach towards answering the main research question is to first explore agent-based modelling of processes of a specific domain, next, to find ways to model interactions between internal processes and social interactions, plus affective and cognitive processes, and to combine different models for these aspects into one new model. Then, tune the model to a specific case study and evaluate it by simulations, experiments and automatic property checking. The main research questions are differentiated into the following sub-questions:

1. How can social interaction processes be modelled using an agent-based approach?
2. How can an intelligent agent support social interaction processes in a team?
3. How can social interaction processes be integrated with internal processes in agent-based models?
4. How can affective processes be integrated with cognitive processes in agent-based models?
5. How can support for groups, based on internal processes and social interactions, be modelled with an agent-based approach?
6. Does the model simulate the real world process or phenomena correctly?
7. Does the model perform better than other similar models?

The different sub-questions are addressed in different parts of this book. Part I is the current introduction in which the need for intelligent agents that can support teams, based on the internal and social dynamics of the team members is described. Part II focuses on agent-based models of emotion contagion and emotion recognition. In Part III, agent-based models that integrate social contagion and internal dynamics are explored. Part IV focuses on the networks of informal caregivers around persons with a depression. In Part V, agent-based models that can simulate team and leadership dynamics are proposed. In Part VI, the results of all agent-based models in this book are summarised and their implications for the field of intelligent agent modelling are stated.
Question 1 (*how can social interaction processes be modelled using an agent-based approach?*), is addressed in Part II. In Chapter 2 it is explored how agent-based models can simulate emotion contagion. In Chapter 11, Part V, the social interactions between a professor and his student is modelled according to group development theory. Furthermore, social interactions between informal caregivers and a patient, and a group of people escaping a building are described in Part III and IV, but are already combined with internal processes.

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Question 2 (*how can an intelligent agent support social interaction processes in a team?*), is addressed in Chapter 2, where positive group emotion is stimulated by an artificial agent, in Chapter 9, where an ambient agent can support informal caregivers to stay healthy and in a positive mood and in Chapter 11, where a team leader is supported in choosing the correct leader style behaviours according to the group’s development level. Note that in Chapters 9 and 11, the social processes are combined with internal processes. That is why in Table 1.1 question 2 is only shown behind Part II and Chapter 2.

Question 3 (*how can social interaction processes be integrated with internal processes in agent-based models?*), is addressed in Part III and IV. Internal processes like emotion-related valuation, and belief and intention generation are integrated with social interactions like emotion and intention contagion in the agent-based models of Chapters 5 and 6. In Chapter 8 and 9, internal processes (e.g., coping and stress buffering) and social interactions (e.g., care giving) of informal caregivers and the patient they take care of are integrated. In Chapter 10 an internal process (emotion regulation) is integrated with social interactions (emotion contagion) as well.
Question 4 (how can affective processes be integrated with cognitive processes in agent-based models?) is most clearly addressed in Chapter 10: the affective process emotion contagion is integrated with the cognitive process of emotion regulation. Also, Chapters 5 and 6 combine the affective process of emotion contagion with cognitive processes of emotion-related valuation (which in itself is already a combination of an affective and cognitive process) and intention and belief generations and their interactions between and amongst them.

Question 5 (how can support for groups based on internal processes and social interactions, be modelled with an agent-based approach?) is addressed in Chapter 9, where an artificial agent can support informal caregivers, based on their internal processes (like coping and stress buffering) and social interactions (like caregiving). Furthermore, the support agent in Chapter 2 that can support group emotion (based on social interactions) is a first step in designing a support agent for the models in Part III, that can support an evacuating crowd based on their social interactions (emotion and intention contagion) and internal processes (e.g. decision making, intention and belief generation).

External validation of the models (question 6: does the model simulate real world process or phenomena correctly?) is performed in Chapters 3, 4, 6, 7 through comparing the model output with the empirical data of the real world processes. For example, the crowd behaviour of the proposed model was compared with that of the actual panicked crowd on Dam Square on the 4th of May 2010. In Chapter 7, the proposed model was tuned to another case study and the amount of fear and sort of intentions it simulated was compared with the real world data of the 7-7 London Bombings. Hypotheses of underlying theories of the emotion contagion models (the broaden-and-build theory, [9]) were tested in Chapter 3. A mix of internal and external validation through property checking and mathematical analysis is performed in chapters 2, 5, 6, 7, 8, 9, 10, 11, 12.

Comparisons of different models (question 7: does the model perform better than other similar models?) are performed in Chapters 4 and 6. In Chapter 4 the performances of humans versus a machine learning algorithm on the same emotion recognition task are compared. In Chapter 6 the performance of the proposed model is compared to the performance of the Helbing model.

1.3 Methodology
The modelling cycle that has been used to design and analyse agent-based models integrating social and internal processes is explained in this section.
1.3.1 Agent-based modelling

An agent is “a computer system that is situated in some environment, and is capable of autonomous action in this environment in order to meet its design objectives”, according to Woolridge and Jennings. [18]. Agents can sense their environment and perform actions in it, which affect the environment, see Figure 1.2 (adapted from Chapter 2 of this book). This definition will be extended in the current research; with that the agent can either represent a human (for example when crowd behaviour is modelled in Part II) or a machine (when it is an artificial ambient support agent, like that in Chapter 9 and 11). A multi-agent system is a collection of agents in an environment, which may communicate or perform activities together. [19].

![Figure 1.2 The interaction between an agent and its environment](image)

The intelligent support agents that are explored, created and envisioned in this book have skills of three kinds: sensing, reasoning and intervention. First, the agent must sense communications, body language, facial expressions, blood pressure and other observable characteristics of the group members. Next it must reason how the group members think and feel; it reasons how the internal and social processes develop and if they are beneficial to the team mood and/or performance. Then, in case team performance and/or mood are in deterioration, it has to intervene somehow. This could be done, for example, by communicating warnings or coaching messages, but also by taking over a task or redirecting it to another person or machine. A possible fourth skill is that of adaptation: some intelligent support agents can adapt their parameters to different individuals or different situations.

The intelligent support agents in this book can consist of multiple components: domain model, analysis model, support model and adaptation model. The domain model describes the phenomena in the natural world that is modelled, for example negative mood contagion, fleeing patterns of crowds
in evacuation scenarios or emotion regulation. By incorporating a domain model within an agent model, the agent gets an understanding of the processes of its surrounding environment, which is a solid basis for knowledgeable human-aware intelligent behaviour. The domain model can be integrated in the agent, by embedding the domain model in three different ways, see Figure 1.3. Here the solid arrows indicate information exchange between processes (data flow) and the dotted arrows the integration process of the domain models within the agent models.

- **analysis model**
  To perform analysis of the humans’ states and processes, by reasoning based on observations (possibly using specific sensors) and the domain model.

- **support model**
  To generate support for the humans, by reasoning based on the domain model and the outcomes (assessments) of the analysis component.

- **adaptation model**
  To tune parameters in the domain model better to the specific characteristics of the humans, by reasoning based on the domain model.

Note that here the domain model that is integrated, refers to a group of agents that represent humans, whereas the agent model in which it is integrated refers to the artificial ambient software agent that can support humans. More details on the integration of the domain model in the agent model can be found in Chapter 2 of this book, where the overall architecture of a supportive agent for emotion contagion in groups is explained.

**Figure 1.3.** Three ways to integrate a domain model within an agent model.
Furthermore, the agent models in the reported research are hybrid models, because they integrate quantitative and qualitative models. Simulations of biological and neurological processes, for example, are often based on numerical (quantitative) methods. Numerical variables describe aspects of the process and how they affect each other over time; for example, how the number of predators affects the number of preys. Agent and knowledge modelling approaches are usually based on logical (qualitative) languages. Declarative models that are based on logic can be specified in representation languages that resemble natural language. This makes the declarative models analysable at a high abstract level. The agent-based models in this book are based on dynamic system models, which are characterised by states and causal-temporal relations between these states [13], [4]. The states can be expressed in qualitative or quantitative format (e.g. ‘more’ or ‘less’ versus numbers) and causal-temporal relations are either formed by numerical dynamic systems based on difference and differential equations or by causal rules based on logical predicate. The models are generic and can be made more specific to certain situations by choosing different parameter settings. Furthermore, the agent-based models of the reported research were formally specified in an implementation-independent conceptual manner and can be implemented in many different programming languages.

1.3.2 Modelling cycle

The modelling cycle that has been used to create agent-based models integrating social and internal processes is explained in this section. Modelling is a creative process; many choices can be made, resulting in different models. Figure 1.4 depicts the general process model followed, in designing and analysing the agent-based models in the reported research: the modelling and simulation cycle [20]. There are two main phases: model design, in which the model is built, and model analysis, in which the model and its behaviour is studied. Note that this modelling cycle can be used to make all sorts of models depicted in Figure 1.3 and that the term analysis in the modelling cycle does not refer to the analysis model in Figure 1.3. The analysis model in Figure 1.3 is an analysis model of the domain model, a kind of meta model. The process of analysing the model itself is meant in the modelling cycle: analysing an agent model. The cycle consists of four activities:

**Design phase:**
1. **Conceptualisation:** determining the main aspects and their relations;
2. **Formalisation:** specifying the detailed model;

**Analysis phase:**
3. **Simulation:** performing experiments with the model to generate traces;
4. **Evaluation:** verifying whether the model behaves as expected.
If the evaluation reveals that the model is not correct, the process starts again with a new conceptualization phase. One can follow the route, but can always take one or more steps back. The first three arrows after the situation in the real world indicate that the next step is the result of the previous step. The last double-sided arrow after simulations traces indicates that the simulation traces are compared with the real world data. The next two subsections discuss the design and analysis phase in more detail.

**Figure 1.4. The modelling and simulation cycle**

1.3.3 **Design phase: conceptualisation and formalisation**

The agent-based models of the reported research were designed by first deciding which process in reality they should model and which patterns or characteristics of this process should be in focus. For example, when the process of emotion contagion is to be modelled, one can choose to focus on the amplification effect or the absorption effect of emotion contagion, or perhaps on both. Next, relevant concepts are identified from relevant literature. In the case of emotion contagion, social diffusion theories and their concepts from Psychology and Cognitive and Social Neuroscience were chosen to be modelled. Concepts like extraversion, introversion, social relationship were chosen, because they affect the contagion process according to psychological and social research. Possible sub processes can be modelled here as well. Thereafter, relationships between concepts were specified. First it was specified if concepts influence each other. This resulted either in a list of statements like “A affects B”, or in a graph in which each concept is depicted as a node and each relationship between concepts as an arrow between nodes.
An example is shown in Figure 1.5. Figure 1.5 is an example that shows which processes lead to an emotional state in the mind and the body. For this example, in the conceptualisation phase, scientific literature and theories would have to be studied that have assumptions and theories about emotion elicitation in the body and mind. From these theories, the most important concepts and relations would have been extracted. The concepts are depicted as the nodes and the relations as the arrows. After making such a figure as Figure 1.5, one can go further with the formalisation phase.

![Figure 1.5. Processes leading to an emotional state](image.png)

After conceptualisation, formalisation took place. In this phase, the details of the specified concepts and relationships are filled in. This was performed in either a numerical representation or logical representation, or a combination of them. In numerical representations, concepts were represented by variables with a value. Relations were rules that specify how the value of one variable can be calculated from the values of other variables. For each concept, variables were defined which can have certain values (often real numbers in the interval [0, 1]). The relations between the concepts required careful thinking. For example, from the psychological and social theories, it was determined how the concepts influence each other. The influence can take several forms, depending on the values that a variable can have and on the time delay related to the effect. For example, a concept $A_2$ that is affected by another concept $A_1$ in a next time step can be specified as follows.

$$A_2(t+\Delta t) = A_2(t) + f(A_1(t), A_2(t))\Delta t$$  \hspace{1cm} (1)

In (1), $t$ is a variable representing the time, $\Delta t$ (delta $t$) stands for a change in the time variable, and $f$ is some function. Similarly, multiple concepts affecting a given concept can be modelled. In case a logical representation was chosen, concepts and their properties were represented by statements that can be true or false. For example, a statement could be `emotion_generated(anger)`, which
Temporal relations between concepts are rules that specify statements such that when at some time point they are true then another statement will be true at another (next) time point. In the LEADSTO language, the temporal relation $A \rightarrow\rightarrow B$ denotes that when a state property $A$ occurs, then after a certain time delay (which for each relation instance can be specified as any positive real number), state property $B$ will occur. [5]. These rules can combine statements in several ways. A few combinations that are often used, are listed below in Table 1.2 (note that for simplicity characters like $A$, $B$, etcetera, are used instead of statements of the form “emotion\_generated(anger)”).

### Table 1.2 Logical statements and their meaning

<table>
<thead>
<tr>
<th>Logical statement</th>
<th>Meaning</th>
</tr>
</thead>
<tbody>
<tr>
<td>$A \land B \rightarrow\rightarrow C$</td>
<td>if $A$ is true and $B$ is true, then $C$ will be true</td>
</tr>
<tr>
<td>$A \lor B \rightarrow\rightarrow C$</td>
<td>if $A$ is true, $B$ is true, or both are true, then $C$ will be true</td>
</tr>
<tr>
<td>$A(X) \rightarrow B(X)$</td>
<td>if $A$ is true for a specific value of $X$, then $B$ will be true for that value of $X$</td>
</tr>
<tr>
<td>not($A$) $\rightarrow\rightarrow B$</td>
<td>if $A$ is not true, then $B$ will be true</td>
</tr>
<tr>
<td>$A(X) \land X &gt; 52 \rightarrow\rightarrow B$</td>
<td>if $A$ is true for a specific value of $X$, which is larger than 52, then $B$ will be true</td>
</tr>
</tbody>
</table>

1.3.4 Analysis phase: simulation and evaluation

The analysis phase of modelling the agent-based models in this book consists of two activities: setting up and running simulation experiments and evaluating the resulting traces. The agent-based models in this book were implemented in Matlab or the LEADSTO software environment [5], which made it possible to simulate the models and generate simulation traces. Before a simulation experiment was performed, a number of steps were taken. First, the pattern or research question to be addressed by the experiment was formulated. Next, several choices could be made with respect to the initial values of variables, the values of the parameters, and values that are added by interaction during the process. A structured plan (a *scenario*), for which values are chosen for initial values and parameter values, was made. Moreover, different scenarios were used in order to compare the outcomes for different circumstances.
After simulation, evaluation of the agent-based model was performed. Evaluation consists of verifying whether the model is a correct representation of the system that it represents and/or if it performs better than other models. This was done in different ways: by formulating properties that hold in the actual situation and check whether they also hold in the model, by comparing the simulation traces of the model with empirical traces of the process in the real world, or by comparing simulation traces of the model with that of other models.

For property checking, the expected properties of a model were listed beforehand, as a starting point for building the model. A distinction can be made between two types of properties:

1. **Quantitative properties**: statements about numerical characteristics of a model. Examples of quantitative properties are: “the unemployment rate never reaches 10 percent”, or “the liquid boils within 4 minutes”, etc.

2. **Qualitative properties**: statements about non-numerical relations or characteristics of the model. Examples of qualitative properties are: “eventually state property X will be true”, “event A always occurs before event B”, “parameter X is always decreasing”, or “the simulation always reaches an equilibrium”, etc.

To specify and automatically check properties against simulation traces, the TTL software environment supporting the hybrid language TTL [6] was used. Also, sometimes a mathematical analysis was performed to prove certain dynamic properties of mathematical models.

For validation by comparison with real world data, empirical traces of the real world data were made, for example, by formalising survivor reports (Chapter 7), manually annotating the crowd behaviour from video (Chapter 5) or by extracting a baseline performance of humans performing the same task as a machine (Chapter 4). These empirical traces could then be compared to the simulation traces of the agent-based model. When the agent-based model was compared to other similar models, statistics was used to compare the performance of multiple models (Chapter 2 and 5). In that way it could be shown which model performs best, in case the behaviour of the different models differs significantly from each other.

Note that in Chapter 3, no agent-based model was designed and evaluated, but an empirical validation of the underlying theories of the emotion contagion models in Part II was performed. In Chapter 3, a standard behavioural research cycle was followed. First hypotheses were formulated and predictions concerning the outcome of the experiment were made. Next, a controlled laboratory experiment was conducted. Then, the results were statistically
analysed and interpreted. Finally, implications for the research field were stated and ideas for future experiments were formulated.

1.4 Thesis outline
This thesis is based on a collection of articles which will therefore have overlap, especially in the introduction of chapters and explanation of the modelling approach in different chapters. One can read it fully, but one can also read separate chapters. The majority of papers are refereed papers that have been published in conference proceedings or journals, or extensions of these papers. All authors are cited in alphabetical order, representing equal contributions to the articles.

This thesis consists of six parts, each focussing on different research questions, stated in sub section 1.2 above. Below, each part of the thesis is outlined.

I. Part I

In the introduction, the main research question within this thesis is introduced: how can an intelligent agent-based system be designed, that gives support to teams, based on their social interactions and internal processes? The contribution of this thesis is the provision and extension of knowledge on how to analyse and design new, innovative computational models for human processes integrating social and individual internal functioning and involving both cognitive and affective elements. This research is innovative, in that it models and validates agent-based models that integrate internal and social dynamics plus affective and cognitive aspects. Usually, computational models do not focus on integrating all of these four aspects. The multiple research objectives are explained, as well as the methodology used to analyse, design and evaluate the agent-based models in this book. Moreover, the contents of each of the six parts of this thesis are outlined.

II. Part II

Part II focuses on agent-based models of emotion contagion and emotion recognition. Chapter 2 consists of the design of agent-based models that can simulate emotion contagion processes in groups. It also proposes an intelligent support agent, which can support a team by helping it to avoid negative emotions in the team. In Chapter 3, some of the underlying theories of emotion contagion are validated. A controlled laboratory experiment was conducted to test the
hypothesis that positive emotions increase a person’s thought-action repertoire, creativity levels and memory and negative emotions narrow them, in comparison to a neutral state. Results showed modest support. This experiment was also conducted to collect natural human speech, for the research in Chapter 4. In Chapter 4, an agent-based model was developed that can recognise different emotions from human speech. This model performed better than humans in the same task. The developed agent-based model can be used in the envisioned intelligent agent: one that is built into your mobile phone and monitors your mood by analysing your voice. This agent can prevent you from depression.

III. Part III

In Part III, agent-based models that integrate social contagion and internal dynamics are explored. In Chapter 5, multiple agent models are proposed that either model the contagion of a single type of individual state (an emotion, intention or belief), or that can model the contagion of multiple individual states at the same time, that also interact with each other, internally or socially. The interactions between emotions, intentions and beliefs during collective decision making in an emergency evacuation were modelled and evaluated by automatic property checking and mathematical analysis. Chapter 6 builds on this work, by extending the agents with actions. The model ASCRIBE is proposed: an Agent-based model of Social Contagion Regarding Intentions Beliefs and Emotions. ASCRIBE was tuned to simulate a real-life incident, where a 20,000 people crowd suddenly ran away in panic and 63 people got injured. Statistical validation and comparisons with the empirical data showed that ASCRIBE reproduces the incident better, when contagion of belief, emotion and intention states are included, than when not. Also, in certain circumstances it performs better than another well-known agent model from the literature: the Helbing model. In Chapter 7, ASCRIBE was tuned to simulate the contagion of intentions and beliefs during another real-life situation: the 7-7 London Bombings. Survivor transcripts were formalised into empirical traces and were compared to the simulation traces of the agent model. Formal comparisons showed that the model closely reproduced the real world scenarios.
IV. Part IV

Part IV focuses on the networks of informal caregivers around persons with a depression. In Chapter 8, an agent model is proposed that can simulate the dynamics of informal care support and receipt interactions among caregivers and care recipients. Concepts like coping, strong ties in the social network and stress buffering showed to have important influences on the stress level of the informal caregiver. In Chapter 9, this work is extended, by proposing an intelligent support agent for informal caregivers. The intelligent agent can generate support actions for specific situations the informal caregiver is in, based on model-based reasoning. In Chapter 10, the integration of emotion regulation and emotion contagion was explored. The proposed agent-based model is innovative, because it integrated affective and cognitive processes. The model was specifically made for negative mood contagion and regulation. Simulations showed that the model is able to realistically produce the processes described in psychological and social literature. The models in Chapter 8, 9 and 10 were evaluated by automatic property checking and mathematical analysis.

V. Part V

In Part V, agent-based models that can simulate team and leadership dynamics are proposed. In Chapter 11, an intelligent support agent that can support group development is designed and evaluated. The proposed model is based on situational leadership theory and monitors and analyses group development overtime. It can propose effective leadership behaviour to the team leader, in order to let the group perform as effectively as it can. The model was evaluated by automatic property checking. In Chapter 12, the communication during crisis management of a real-life incident “fire in the Amsterdam Airport Schiphol train tunnel” was formalised into an empirical trace. Due to miscommunication, three trains had to hold for more than thirty minutes in the train tunnel during a fire. This led to very anxious passengers and was a near miss situation: many people could have died if the fire would not have gone out by itself. It is shown how automatic property checking can be an efficient way to analyse (mistakes in) communication during incident management. Also, it is a first step towards designing an agent-based model that can simulate multiple incident management scenario’s to find out which management style is most effective.
VI. Part VI

In Part VI, the results of all agent-based models in this book are summarised and their implications for the field of intelligent agent modelling are stated. Ideas and plans for future work based on this thesis are presented.

References


[20] Figure made by Michel Klein. The Modelling Cycle is used in Education Material of the Course “Introduction in Modelling and Simulation” of the Bachelor Lifestyle Informatics at VU University, Amsterdam.
Part II: Modelling Emotion Contagion and Emotion Recognition

Abstract. Part II focuses on agent-based models of emotion contagion and emotion recognition. Chapter 2 consists of the design of agent-based models that can simulate emotion contagion processes in groups. It also proposes an intelligent support agent, which can support a team by helping it to avoid negative emotions in the team. In Chapter 3, some of the underlying theories of emotion contagion are validated. A controlled laboratory experiment was conducted to test the hypothesis that positive emotions increase a person's thought-action repertoire, creativity levels and memory and negative emotions narrow them, in comparison to a neutral state. Results showed modest support. This experiment was also conducted to collect natural human speech, for the research in Chapter 4. In Chapter 4, an agent-based model was developed that can recognise different emotions from human speech. This model performed better than humans in the same task. The developed agent-based model can be used in the envisioned intelligent agent: one that is built into your mobile phone and monitors your mood by analysing your voice. This agent can prevent you from depression.
Chapter 2 - Agent-Based Modelling of Emotion Contagion in Groups

Tibor Bosse, Rob Duell, Zulfiqar A. Memon, Jan Treur, C. Natalie van der Wal

Abstract To avoid the development of negative emotion in their teams, team leaders may benefit from being aware of the emotional dynamics of the team members. As a first step, this chapter uses an agent-based approach to formalize and simulate emotion contagion processes within groups, which may involve absorption or amplification of emotions of others. The obtained computational model is analysed both by explorative simulation and by mathematical analysis. In addition, it is shown how the model can be integrated within a computational ambient agent model to monitor and predict group emotion levels over time and propose group support actions based on that.

Parts of this chapter have been or will be presented in:
2.1 Introduction

The occurrence of emotion contagion in groups is a social phenomenon, where emotions of group members can be absorbed by other group members, but also can be amplified so that levels of emotion may occur that may substantially exceed the original emotion levels of group members. How to avoid such trends for negative emotions and how to stimulate them for positive emotions can be a real challenge for both group members and group leaders. This chapter first presents an analysis and a computational model for the occurrence of emotion contagion in groups. In addition, it is shown how this model can and has been integrated within a computational ambient agent model to support group leaders. The ambient agent can predict and analyze the team’s emotional level for present and future time points. In case a team’s emotional level is found (to become) deficient compared to a certain norm, the ambient agent proposes the team leader to take some measures.

Many definitions of emotions exist today. In this chapter emotions are defined as being intense and short-lived and focused on a specific target or cause [12]. Emotions can sometimes transfer into moods, which are global positive feelings which can last a few moments up to a few weeks. Emotions, moods and other related concepts such as feeling traits and personal tendencies, are gathered under the general term affect. All terms that fall under the most general term affect are further explained in [3]. In the current work only emotions are into focus, with the possible extension into moods. Emotions allow humans to respond quickly and efficiently to events that affect their welfare [20]. In addition, they provide us with information about others’ behavioural intentions, and script our social behaviour. Research on the idea that emotion has a strong social component as well, which can influence interactions, is found in, e.g. [15], [16]. The process of emotion contagion, in which a group member influences the emotions of another group member (and vice versa), through the conscious or unconscious induction of emotion states [27], is a primary mechanism through which individual emotions create a collective emotion. This process has been described as an inclination to mimic the gestural behaviour of others, to “synchronize facial expression, utterances and attitudes” [16]. Emotion contagion has been shown to occur in many cases varying from emotions in small groups to panicking crowds; see [1], [2], [29], [21].

Emotion contagion has found a biological foundation in recent neurological findings on the mirroring function of certain neurons (e.g., [18], [19], [25]. Mirror neurons are neurons which, in the context of the neural circuits in which they
are embedded, show both a function to prepare for certain actions or bodily changes and a function to mirror states of other persons. They are active not only when a person intends to perform a specific action or body change, but also when the person observes somebody else intending or performing this action or body change. This includes expressing emotions in body states, such as facial expressions for emotions. For example, there is strong evidence that (already from an age of just 1 hour) sensing somebody else’s face expression leads (within about 300 milliseconds) to preparing for and showing the same face expression ([13], p. 129-130). The idea is that these neurons and the neural circuits in which they are embedded play an important role in social functioning and in (empathic) understanding of others; (e.g., [18], [25]). The discovery of mirror neurons is often considered a crucial step for the further development of the discipline of social cognition, comparable to the role the discovery of DNA has played for biology, as it provides a biological basis for many social phenomena; cf. [18]. Indeed, when states of other persons are mirrored by some of the person’s own states that at the same time are connected via neural circuits to states that are crucial for the own feelings and actions, then this provides an effective basic mechanism for how in a social context persons fundamentally affect each other’s actions and feelings.

The positive effects of emotions have been investigated empirically in [10], where it is hypothesized that positive emotions trigger upward spirals toward enhanced emotional well-being. This prediction is based on Frederickson’s broaden-and-build theory [11]. The broaden hypothesis states that positive emotions broaden people’s momentary mind-sets: the scopes of attention, cognition, action and the array of percepts, thoughts, and actions presently in mind are widened. This in turn, serves to build their enduring personal resources. In this way the short term effect of positive emotions can develop from a short-term effect into a longer lasting positive upward spiral. The complementary narrowing hypothesis predicts the reverse pattern: negative emotions shrink people’s momentary thought-action repertoires. In turn, also in the reverse pattern the momentary or ‘beginning’ negative spiral can build into a longer lasting negative spiral. Support for the broaden and narrowing hypotheses can be found in [9]. The build hypothesis expresses that positive emotions encourage people to discover and explore new ways of thinking and action, by which they are building their personal resources such as socio-emotional and, intellectual skills. The broaden hypothesis can predict upward trends in emotional well-being of a person, which the authors [9], [10], [11] and many other researchers in the field of positive psychology investigate. In [10], the authors demonstrated that initial experiences with positive affect can improve broad-minded-coping, which in turn can predict increases in positive affect over time, creating an upward trend towards improved emotional well-
This chapter first gives a brief overview of the architecture of the proposed agent based models in Section 2.2. Next, in Section 2.3, a multi-agent model is proposed, that formalizes and simulates emotion contagion within groups, and can represent two different types of emotion contagion processes: emotion absorption and emotion amplification within groups. Then it is shown how this computational model can be used in applications within a teamwork context, supported by an intelligent ambient agent. In Section 2.4 simulation results for the model are presented and in Section 2.5, the models are analyzed mathematically. Section 2.6 addresses formal verification of the emotion contagion model and the simulation results. Section 2.7 explains a formalized model of group emotion contagion processes. Section 2.8 describes how the model for emotion contagion has been integrated within an existing ambient agent model. In Section 2.9, simulation results are discussed for the resulting ambient agent model. Section 2.10 concludes the chapter with a discussion.

2.2 Overall Architecture and Different Models Used

In this chapter agent based models for domain, analysis and support models of emotion contagion will be proposed. This section will explain the architecture used for these models. A domain model describes the phenomena in the natural world that are modelled, in this case emotion contagion. The integration of a domain model in an ambient agent model takes place by embedding the domain model in certain ways within the agent model. By incorporating a domain model within an agent model, the agent gets an understanding of the processes of its surrounding environment, which is a solid basis for knowledgeable human-aware intelligent behaviour. Three different ways to integrate domain models within an agent model are considered; see Figure 2.1. Here the solid arrows indicate information exchange between processes (data flow) and the dotted arrows the integration process of the domain models within an agent model.

- **analysis model**
  To perform the analysis of humans’ states and processes by reasoning based on observations (possibly using specific sensors) and the domain model.

- **support model**
  To generate support for the humans, by reasoning based on the domain model.

- **adaptation model**
  To tune parameters in the domain model better to the specific characteristics of the humans, by reasoning based on the domain model.
Note that here the domain model that is integrated refers to a group of agents, the humans considered, whereas the ambient agent model in which it is integrated refers to the ambient software agent.

**Analysis Model**

A crucial element of ambient agents is that they collect and infer information about the humans’ functioning. Some aspects of the states and processes related to the humans’ functioning can be directly observed, but often many relevant aspects only can be indirectly derived from such observation information. For such derivations it is useful to have a domain model integrated within the analysis model, which can be used to estimate states of the human (for past, present and future time points). Given these estimated human states, an assessment is made to verify whether there is any reason to consider support. As an example, the level of positive emotions in the group may be assessed as too low.

**Support Model**

For an ambient agent to have some beliefs and assessments about the humans’ internal state is one thing, but to be of any help, actions are also needed to change or avoid undesirable states. To generate actions that fit to the results of the analysis, a support model is used by the ambient agent. In this model, based on the assessments and beliefs on the human’s states, appropriate support actions are determined. For example, a group member with strong expressivity for positive emotions may be given a more central role in the group, so that more contagion will take place.
Adaptation Model

Domain models often include a number of parameters that represent certain characteristics of the processes modelled. In principle, for a given domain process such characteristics are assumed constant; they allow the tuning of a domain model to specific situations, for example, specific types of human personalities. An ambient agent may have beliefs about these characteristics and use them in its reasoning processes. For a domain model the parameters involved are assumed fixed, but beliefs about them may change over time.

Beliefs on parameters used by an ambient agent in its analysis and support models need not (exactly) correspond to the actual parameters for the domain model that correspond to reality. Within an ambient agent the beliefs about such parameters may be questioned in the light of observations made. For example, if a certain growth factor for a population is believed, and it is observed that after some time the population is much smaller than predicted on the basis of the believed growth factor, the ambient agent may want to adapt its belief on the growth factor by replacing this belief by a belief in a lower value. When beliefs on parameters used by the ambient agent substantially differ from reality, the agent may make errors in its analysis and in its support actions. Often it is not easy to estimate such parameters beforehand (at design time). Therefore it is better to design an ambient agent in such a way that it can learn by identifying errors in parameter beliefs, and after discovering them, adapting these beliefs in order to obtain more correct beliefs on the parameters (at runtime). Two main questions to be addressed are:

1. How does the agent get information on the (extent of) deviation of the model from reality?
2. How can it relate such identified deviations to adaptations required in parameter beliefs to compensate for them?

For an answer to the first question, in this section it is assumed that at certain time points (but not necessarily always) information becomes available, as observations for the ambient agent. A deviation can be obtained as a difference between observation and prediction on the basis of a prediction model similar to the analysis model using the given beliefs on the parameters. For the second question a deviation found has to be related to the beliefs on the parameters. Although it may be often assumed that in the numerical case the larger the deviation, the more the parameter value has to be adapted, still it is not clear in which direction (positive or negative) and to which extent such an adaptation of a parameter value is needed. In particular, when more than one parameter is involved this is a nontrivial challenge.
2.3 The Emotion Contagion Model

Modelling group emotion can be done at the level of the group or at the level of the individuals, which has been named respectively the top-down and bottom-up approach [2]. The bottom-up perspective sees group emotion as the sum of its parts, affected by the homogeneity or heterogeneity of the group and the mean emotions of the group members. Individual differences play an important role, such as specific personality traits and the underlying brain mechanisms. The top-down approach defines group emotion as being different from the sum of its individual parts. The authors describe this as that diverse emotional tendencies of individuals are submerged into a group emotion and the emotional character of the group can be more extreme than the individual tendencies. The model for emotion contagion introduced in this section subsumes different types of emotion contagion, varying from emotion absorption which occurs when group members adapt their emotion levels to each other by a kind of averaging process, to emotion amplification, in which case group members can use other group members’ emotion as trigger to generate higher or lower levels of emotions than available in the group. These two different types of models can be linked to a certain degree with the top-down and bottom-up approach defined in [2], emotion absorption being more a bottom-up approach and emotion amplification being more a top-down approach of modelling group emotion contagion. The model distinguishes multiple factors that influence emotion contagion. In [1] (following [21]) Barsade describes an informal model of emotion contagion in which the emotion being expressed and transferred between group members is characterized by the valence (positive or negative) and the energy level with which the emotion is expressed. Furthermore Barsade [1] suggests two categories of contagion mechanisms: automatic subconscious contagion through mimicry and feedback and conscious transfer through social
comparison of moods and appropriate responses in groups, mediated by attention. Regardless of the mechanisms employed, it is claimed that the type of emotion and the degree of emotion contagion in groups, is influenced by the emotional valence and the emotional energy.

Inspired by these theories, in this section a computational model of emotion contagion is proposed. First a number of aspects are distinguished that play a role in the contagion, varying from aspects related to the sender, the channel between sender and receiver and the receiver of the transferred emotion. Accordingly, the model distinguishes three parts in the process of transfer of emotion and related parameters: a sender $S$, a receiver $R$, and the channel from $S$ to $R$ (see Fig. 2.2 and Table 2.1).

Table 1.1 Parameters for aspects of emotion contagion

<table>
<thead>
<tr>
<th></th>
<th>Emotion state</th>
<th>Characteristics</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Sender</strong></td>
<td>current level of the sender’s emotion</td>
<td>$q_S$ extent to which the sender expresses the emotion $\varepsilon_S$</td>
</tr>
<tr>
<td><strong>Channel</strong></td>
<td></td>
<td>the strength of the channel from sender to receiver $\alpha_{SR}$</td>
</tr>
<tr>
<td><strong>Receiver</strong></td>
<td>current level of the receiver’s emotion</td>
<td>$q_R$ openness or sensitivity for received emotion $\delta_R$</td>
</tr>
<tr>
<td></td>
<td></td>
<td>bias to adapt emotions upward or downward $\beta_R$</td>
</tr>
<tr>
<td></td>
<td></td>
<td>tendency to amplify emotions $\eta_R$</td>
</tr>
</tbody>
</table>

The aspect $\varepsilon_S$ depends on how introvert or extravert, expressive, active and energetic the person is. It represents the degree to which a person transforms internal emotion into external expression. In this sense, an introvert person will induce a weaker contagion of an emotion than an extravert person. The aspect $\alpha_{SR}$ depends on the type and intensity of the contact between the two persons (e.g., distance vs. attachment). The aspect $\delta_R$ indicates the degree of susceptibility of the receiver: the extent to which the receiver allows the emotions received from others to affect his own emotion, and how flexible/persistent the receiver is emotionally. The aspect $\eta_R$ describes the tendency to amplify emotions, when triggered by received emotions. When it is 0 the person does not amplify emotion, but only absorbs them; when it is 1 it does not absorb emotions but only amplifies them. The aspect $\beta_R$ describes the bias when amplifying emotions (more positive or more negative), when triggered by received emotions.

As a first step, all aspects have been formalized numerically by numbers in...
the interval $[0, 1]$. In addition, the parameter $\gamma_{SR}$ is used to represent the strength by which an emotion is transferred to $R$ from sender $S$. It is assumed to depend on expressiveness $\varepsilon_s$, channel strength $\alpha_{SR}$, and openness $\delta_R$, as follows:

$$\gamma_{SR} = \varepsilon_s \alpha_{SR} \delta_R$$  \hspace{1cm} (1)

The stronger the channel, the higher $\alpha_{SR}$ and the more contagion takes place. The model works as follows: if gamma is set to 0 there is no contagion, if $\gamma_{SR}$ is 1, there is a maximum strength of contagion. If $\gamma_{SR}$ is not 0, there is contagion and the higher the value, the more contagion takes place. In this way, the parameter $\gamma_{SR}$ can create the behaviour as formulated by hypothesis (1) and (2) from [1]. In a way $\gamma_{SR}$ expresses the energy by which an emotion is being expressed and transferred. Interestingly this $\gamma_{SR}$ depends on situational factors (processes and influences) at both group and individual level. The overall strength by which emotions from all the other group members are received by $R$ in a group $G$, indicated by $\gamma_{R}$, is defined as:

$$\gamma_{R} = \sum_{S \in G \setminus \{R\}} \gamma_{SR} \hspace{1cm} (2)$$

The proposed model can simulate upward and downward emotional spirals through mechanisms, with which not only an individual agent, but also the whole group of agents can get to a higher or lower level of emotion. Each agent transfers an emotion value $q$ between 0 and 1. The model makes it possible for each agent in certain situations to approximate values like 0 and 1, or values in between. Each agent will reach its own emotional equilibrium within the group. Suppose $G$ is a group of agents. The dynamics of an agent $R$’s emotion level is described as

$$\frac{dq_R}{dt} = \gamma_{R} \left[ \eta_R (\beta_R PI + (1-\beta_R) NI) + (1-\eta_R) q_R^* - q_R \right].$$  \hspace{1cm} (3)

Here

$$q_R^* = \sum_{S \in G \setminus \{R\}} w_{SR} q_S \hspace{1cm} (4)$$

is a weighted sum of the emotion levels of the other group members with weights

$$w_{SR} = \varepsilon_s a_{SR} / \sum_{C \in G \setminus \{R\}} \varepsilon_C a_{CR} \hspace{1cm} (5)$$
The upward or downward direction of the change in an agent’s emotional level over time depends on the bias parameter $\beta_R$ and the speed of ascend or descend on parameter $\gamma_R$. Furthermore, to determine amplification, $PI$ and $NI$ are the positive and negative impact of received emotion from the other group members respectively, which will be specified in more detail below. The parameter $\beta_R$ defines the overall impact as a weighted combination of the two contributions. By varying the values of the $\beta_R$’s, upward as well as downward spirals can be simulated. If $\beta_R = 1$ then the receiver is only susceptible for positive impact. If $\beta_R = 0$, then the receiver is only susceptible to negative impact. Any number between 0 and 1 represents a person who is more or less susceptible to positive and negative impact. E.g., if $\beta_R = 0.8$, the agent will be infected by 80% with $PI$ and by 20% with $NI$. In more detail the positive and negative impacts of the other group members are defined as:

$$PI = 1 - (1-q_R^*)(1-q_R)$$

$$NI = q_R^* q_R$$

By filling these in the equation (3), the detailed set of equations for group $G$ is for all $R \in G$:

$$\frac{dq_R}{dt} = \gamma_R \left[ \eta_R (\beta_R (1-(1-q_R^*)(1-q_R)) + (1-\beta_R) q_R^* q_R) + (1-\eta_R) q_R^* - q_R \right]$$

Note that the model presented so far represents the emotional states of all agents within a group separately; the question of how these separate individual emotional states can be interpreted and aggregated, in order to assess the collective emotional state of a group, is addressed in Section 2.6.

2.4 Simulation Results for Emotion Contagion

In this section some simulation results of emotion contagion processes are discussed, first for the emotion absorption model, and next for the emotion amplification model that generates emotion contagion spirals.

2.4.1 Simulation Results for Emotion Absorption

A large number of simulations have been performed, using numerical simulation software, resulting in a variety of interesting patterns. These patterns are described in this section. The occurrences of a number of typical patterns were mathematically proven (under certain conditions) and are presented in Section 2.5. In this section some of the simulation results are
discussed for the case of the absorption: \( \eta_R = 0 \) for all \( R \). Simulation results for the case of amplification (\( \eta_R = 1 \) for all \( R \)) will be presented in Section 2.4.2.

![Emotion absorption: general pattern](image)

**Figure 2.3.** Simulation trace for emotion absorption (\( \eta_R = 0 \) and \( \gamma_R = 1 \) for all \( R \)). See Theorem 3, Section 2.5.1

Simulations shown here are for a group of 3 agents a, b, and c. Time is at the horizontal axis, and the emotion level at the vertical axis. A first pattern found is that when the \( \gamma_R \) for all agents are not 0 (in this case they are all 1), the emotion levels of all of them approximate the average of their initial emotion levels; hereby the speed depends on the \( \delta_R \) (susceptibility) and \( \varepsilon_s \alpha_{SR} \) (see Figure 2.3). The occurrence of this pattern has been confirmed mathematically; see Theorem 3 in the Section 2.5.

![Absorption with agent a not open](image)

**Figure 2.4** Simulation trace 2 for emotion absorption (\( \eta_R = 0 \) and \( \delta_a = 0, \delta_b \neq 0, \delta_c \neq 0 \))
A very specific pattern happens when all $\gamma_R$ are 0, in this case all agents will have equilibria that are equal to their individual initial emotional levels. In other words: the emotional levels of all agents will not change at all; see Theorem 1 in the next section. (not presented in a figure here). Another situation (see Figure 2.4) occurs when agent a has $\delta_a$ set to 0 and the other agents have this parameter $\neq 0$. This situation represents that agent a is not open to receive emotions, but can send emotions. As a result agent a’s initial emotion level will remain the same. Furthermore, the agents b and c will eventually reach the equilibrium of agent a, which is equal to its initial emotion level.

In Figure 2.5 it is shown that when agent a and b both have $\delta_R$ set to 0, agent c will reach a value in between a and b’s initial emotion values. The actual value that agent c will reach, depends on the settings of the parameter settings for all agents. This situation represents a case, where two agents do not change their emotional level, because they are only open to sending emotions, but not to receiving emotions. As a result the third agent is forced to reach a value in between the emotional levels of the others. A next situation (see Figure 2.6) is one where $\delta_a$ and $\epsilon_a$ are set to 0. This represents agent a being bidirectionally excluded from emotion contagion: (s)he can not receive or send emotions. The agents b and c, are forced to go to a certain average in between their initial emotion values. The exact value they will reach, depends on the settings of their $\delta_R$ (susceptibility) and $\epsilon_{SR}$.

![Absorption with agents a and b not open](image)

**Figure 2.5** Simulation trace 3 for emotion absorption ($\eta_R = 0$ and $\delta_R (a, b, c) = (0, 0, 0.5)$). See Theorem 2, Section 2.5.1
2.4.2 Simulation Results for Emotion Amplification

Inspired by the momentary emotion (contagion) effects that can turn into long lasting upward or downward emotional spirals in [11], for the case of amplification ($\eta_R = 1$ for all $R$) the proposed model can simulate both upward and downward emotional spirals. A large number of simulations have been performed, using numerical simulation software, resulting in a variety of interesting patterns. In this section some of the simulation results are discussed. The next section presents results of a mathematical analysis, in which for most patterns their occurrence was proven, under certain conditions.

---

Figure 2.6 Simulation trace 4 for emotion absorption ($\eta_R = 0$ and $\delta_a = \varepsilon_a = 0$)

Figure 2.7 Simulation trace 1 (all $\beta = 0$, all $\delta_a = 0.6$, $\delta_b = 0.7$, $\delta_c = 0.8$, and all $w_{DC} = 0.2$). See Theorem 2, Section 2.5.2
Figure 2.8 Simulation trace 2 ($\beta(a, b, c) = (0, 1, 0.8)$, all $\delta_{\hat{R}}=0.9$, all $w_{DC}=0.9$)

Figure 2.9 Simulation trace 3 (all $\beta=0.5$, all $\delta_{\hat{R}}=0.1$, all $w_{DC}=0.9$). See Theorem 3, Section 2.5.2
All simulations presented are for a group of 3 agents, infecting each other with the same emotion. A first pattern found is that when the bias parameters $\beta$ of all three agents are set to 0 (strong downward bias), the emotion levels of all of them will approximate 0, with speed depending on the $\delta_R$ (susceptibility) and $\varepsilon, \alpha_{SR}$ (individual and group characteristics); see Figure 2.7 (with time on the x-axis and emotion strength on the y-axis). The reverse happens when all $\beta$'s are set to 1, then all agents will achieve an equilibrium of 1. The occurrence of these patterns have been confirmed mathematically in Theorem 2 discussed in the next section.

Another situation occurs when the three agents have their $\beta$'s set to: 0, 1 and any other number. A situation was simulated in which agent $a$ is susceptible only with negative impact ($\beta = 0$), agent $b$ is only susceptible with positive impact ($\beta = 1$), and agent $c$ is susceptible to more positive than negative impact ($\beta = 0.8$). In Figure 2.8, it is shown that in this case the equilibrium values match the agents’ values of $\beta$. The speed of ascend or descend, depends on the susceptibility of the agent (setting of $\delta_R$) and the situational factors at the individual and group level (represented by $\varepsilon, \alpha_{SR}$). This illustrates the more general result expressed in Proposition 3, discussed in the next section. A next simulated situation (see Figure 2.9) is one where all three agents are equally susceptible to positive and negative impact, by setting every agent’s $\beta$ to 0.5. In this situation all agents approximate an equilibrium value at 0.6; this equilibrium is the average of the initial emotional level; in this a case of neutral bias values in fact absorption takes place. This simulation
illustrates Theorem 3, discussed in the next section. In the next situation presented the settings are: $\beta(a, b, c) = \beta(1, 0.3, 0.8)$, as shown in Figure 2.10. This represents a situation where agent $a$ is only or fully susceptible to positive impact, agent $b$ is susceptible more towards negative impact and agent $c$ is more susceptible towards positive impact. Interestingly, agent $b$ does not have an equilibrium of 0 or below 0.5: all agents have an equilibrium of 1. An indication for the height of the equilibrium could be the average $\beta$, which is 0.7 in this situation. This makes it possible to lift the emotional level of all group members to make the group-as-a-whole achieve an upward spiral [10]. In the mathematical analysis such behavior has been proved to occur (between two agents) in Theorem 4.

2.5 Mathematical Analysis for the Emotion Contagion Model

In this section a mathematical analysis for the emotion contagion models are presented. First the emotion absorption model is addressed, and next the emotion amplification model.

2.5.1 Mathematical Analysis for the Emotion Absorption Model

This section presents some of the results of a mathematical analysis of the model that has been made. Note that $\gamma_A = 0$ iff $\sum_B \epsilon_B \alpha_{BA} \delta_A = 0$ iff $\epsilon_B \alpha_{BA} \delta_A = 0$ for all $B \neq A$. This means that $\gamma_A = 0$ can only occur when for each $B \neq A$ either $\epsilon_B = 0$ or $\alpha_{BA} = 0$ or $\delta_A = 0$. This can be interpreted in the sense that $A$ is isolated from emotional impact of all group members. In such a special case $q_A$ will always be in an equilibrium state.

**Theorem 1 (No change when $\gamma_A = 0$)**

If $\gamma_A = 0$ then the emotion value for $A$ will be in an equilibrium right from the start.

Next, conditions on monotonicity are addressed. Assuming $\gamma_A > 0$, from the equations it follows that $dq_A/dt \geq 0$ if and only if $q_A^* \geq q_A$. In particular, for $A$ with the lowest $q_A$ it holds $q_B \geq q_A$ for all $B \neq A$, and therefore via $q_A^* = \sum_B w_{BA} q_B \geq \sum_B w_{BA} q_A = q_A$ it follows that $q_A$ is monotonically increasing. Similarly the highest $q_A$ is monotonically decreasing.

**Theorem 2 (Monotonicity Conditions)**

Suppose $\gamma_A > 0$. Then the following hold:

(a) $q_A$ is monotonically increasing iff $q_A^* \geq q_A$

(b) $q_A$ is strictly monotonically increasing iff $q_A^* > q_A$
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(b) \( q_A \) is monotonically decreasing iff \( q_{A'} \leq q_A \)
\( q_A \) is strictly monotonically decreasing iff \( q_{A'} < q_A \)

(c) If \( q_B \geq q_A \) for all \( B \neq A \), then \( q_A \) is monotonically increasing.
If in addition \( q_B > q_A \) for at least one \( B \neq A \), then \( q_A \) is strictly increasing.

(d) If \( q_B \leq q_A \) for all \( B \neq A \), then \( q_A \) is monotonically decreasing.
If in addition \( q_B < q_A \) for at least one \( B \neq A \), then \( q_A \) is strictly decreasing.

Next, equilibria are addressed for \( \gamma_A > 0 \). When at some point in time all \( q_A \) are the same, then from Theorem 2(c) and (d) it follows that they are both (non-strictly) monotonically increasing and decreasing, so they are in an equilibrium. Moreover, from Theorem 2(c) and (d) it follows that as long as the values of the \( q_A \) are different, then the lowest and highest values keep on changing (strictly increasing, resp. decreasing), so are not in an equilibrium. This implies the following identification of equilibria.

**Theorem 3 (Equilibria when \( \gamma_A > 0 \) for all \( A \))**

Suppose \( \gamma_A > 0 \) for all \( A \). Then the equilibria are the cases where all \( q_A \) are equal. Equilibria are reached between the lowest and highest initial value. In some cases the equilibria are the average of the initial values, due to preservation of the (overall) sum of the emotion levels:
\[
\sum_{A \in G} q_A(t') = \sum_{A \in G} q_A(t) \quad \text{for all } t \text{ and } t' \text{ or } \sum_{A \in G} q_A(t + \Delta t) = \sum_{A \in G} q_A(t) \text{ for all } t \text{ and } \Delta t.
\]
Taking the sum of the equations, the criterion for preservation is
\[
\sum_{A \in G} \gamma_A(q_{A'} - q_A) = 0 \quad \text{or} \quad \sum_{A \in G} \gamma_A q_{A'} = \sum_{A \in G} \gamma_A q_A
\]
Now
\[
\gamma_A w_{BA} = \sum_{C \in G \setminus \{A\}} \gamma_{CA} w_{BA} = \sum_{C \in G \setminus \{A\}} \varepsilon_C \alpha_{CA} \delta_A w_{BA}
= (\sum_{C \in G \setminus \{A\}} \varepsilon_C \alpha_{CA}) \delta_A / \sum_{C \in G \setminus \{A\}} \varepsilon_C a_{CA}
= \varepsilon_B a_{BA} \delta_A \gamma_{BA}
\]
Therefore
\[
\gamma_A q_{A'} = \sum_{B \in G \setminus \{A\}} \gamma_A w_{BA} q_B = \sum_{B \in G \setminus \{A\}} \gamma_{BA} q_B
\]
and taking the sum
\[
\sum_{A \in G} \gamma_A q_{A'} = \sum_{A \in G} \sum_{B \in G \setminus \{A\}} \gamma_{BA} q_B = \sum_{B \in G} \sum_{A \in G \setminus \{B\}} \gamma_{BA} q_B = \sum_{B \in G} \gamma_{BA} q_B
\]
It follows that the criterion for overall emotion preservation is equivalent to
\[
\sum_{A \in G \setminus \{B\}} \gamma_{BA} = \gamma_B = \sum_{A \in G \setminus \{B\}} \gamma_{AB} \quad \text{for all } B
\]
which in terms of the basic parameters is equivalent to
\[
\sum_{A \in G \setminus \{B\}} \varepsilon_B a_{BA} \delta_A = \sum_{A \in G \setminus \{B\}} \varepsilon_A a_{AB} \delta_B \quad \text{for all } B.
\]
**Theorem 4 (Preservation of overall emotion)**

The following are equivalent:

(i) The overall emotion in the group is preserved

(ii) \[ \sum_{A \in G \setminus \{B\}} \gamma_{BA} = \sum_{A \in G \setminus \{B\}} \gamma_{AB} \] for all \( B \).

(iii) \[ \sum_{A \in G \setminus \{B\}} \varepsilon_B a_{AB} \delta_A = \sum_{A \in G \setminus \{B\}} \varepsilon_A a_{AB} \delta_B \] for all \( B \).

When these conditions are satisfied, an equilibrium is reached where each emotion level is the average of the initial emotion levels. The conditions are satisfied in particular when all \( \gamma_{BA} \) are equal, or when, more specifically, all \( \varepsilon_A \) are equal, all \( a_{AB} \) are equal and all \( \delta_B \) are equal. Finally, it is analyzed under which conditions the emotion values stay within the interval \([0, 1]\) (closure property). It can easily be verified that the expression describing change reaches its maximum for \( \varepsilon_A = a_{AB} = \delta_B = q_s = 1 \) and \( q_R = 1 \). Similarly, this function reaches its minimum for \( \varepsilon_A = a_{AB} = \delta_B = q_R = 1 \) and \( q_s = 0 \). Using this, the following equations for upper and lower bounds are obtained:

\[
(1 - (#(G) - 1)) \Delta t = q_{\text{min}} \leq q_R(t + \Delta t) \leq q_{\text{max}} = ( #((G)-1)) \Delta t
\]

In order to maintain the closure property for emotion contagion in the absorption model, \( q_{\text{max}} \) has to be constrained to 1 and \( q_{\text{min}} \) to 0. Therefore, respectively:

\[
(#(G)-1).\Delta t \leq 1 \quad \text{and} \quad (1 - (#(G) - 1)) \Delta t \geq 0
\]

both lead to the same constraint \( \Delta t \leq 1/((#(G) - 1)). \) So, as long as this constraint is maintained, the closure property holds for the absorption model:

**Theorem 5 (Closure property)**

The emotion values generated remain in the interval \([0, 1]\) if \( \Delta t \leq 1/( #(G) - 1) \).

2.5.2 Mathematical Analysis for the Emotion Amplification Model

This section presents some of the results of a mathematical analysis of the model that has been made. First, the following conditions on monotonicity have been found.

**Proposition 1 (Monotonicity Conditions)**

(a) If \( \beta_A = 0 \) then \( q_A(t) \) is always monotonically decreasing;
   it is strictly decreasing when \( q_A^*(t) < 1 \) and \( q_A(t) > 0 \).

(b) If \( \beta_B = 1 \) then \( q_B(t) \) is always monotonically increasing;
   it is strictly increasing when \( q_B^*(t) > 0 \) and \( q_B(t) < 1 \).

(c) If \( \beta_A \leq 0.5 \) and \( q_A^*(t) \leq q_A(t) \) then \( q_A(t) \) is monotonically decreasing;
   it is strictly decreasing when \( q_A^*(t) < q_A(t) \).
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(d) If $\beta_B \geq 0.5$ and $q_B^*(t) \geq q_B(t)$ then $q_B(t)$ is monotonically increasing; it is strictly increasing when $q_B^*(t) > q_B(t)$.

Next, equilibria have been investigated. First, conditions have been established for the case of an equilibrium with one of the emotion values 0 or 1.

**Proposition 2**

Suppose all $w_{SR}$ are nonzero. Then for an equilibrium the following holds:

(a) If $q_A = 0$ then $\beta_A = 0$ or $q_C = 0$ for all $C$

(b) If $q_B = 1$ then $\beta_B = 1$ or $q_C = 1$ for all $C$

Based on this, the following theorem provides the possibilities for equilibria concerning those subgroups with $\beta$ is 0 or 1.

**Theorem 1 (Equilibria for members for which $\beta$ is 0 or 1)**

Suppose all $w_{SR}$ are nonzero. Let the two subsets $S_0, S_1 \subseteq G$ be given by

$S_0 = \{ A \in G \mid \beta_A = 0 \}$ \hspace{1cm} $S_1 = \{ B \in G \mid \beta_B = 1 \}$

Then for an equilibrium the following holds:

(a) If $A \in S_0$ then $q_A = 0$ or $q_C = 1$ for all $C \neq A$. If $B \in S_1$ then $q_B = 1$ or $q_C = 0$ for all $C \neq B$.

(b) If $\#(S_0) \geq 2$, i.e., there are at least two members $A_1$ and $A_2$ with $\beta_{A1} = 0$ and $\beta_{A2} = 0$, then either $q_A = 0$ for all $A \in S_0$ or $q_C = 1$ for all $C \in G$.

(c) If $\#(S_1) \geq 2$, i.e., there are at least two members $B_1$ and $B_2$ with $\beta_{B1} = 1$ and $\beta_{B2} = 1$, then either $q_B = 1$ for all $B \in S_1$ or $q_C = 0$ for all $C \in G$.

(d) If $\#(S_0) \geq 2$ and $\#(S_1) \geq 2$, then there are three possibilities:

(i) $q_C = 0$ for all $C \in G$

(ii) $q_C = 1$ for all $C \in G$

(iii) $q_A = 0$ for all $A \in S_0$ and $q_B = 1$ for all $B \in S_1$

In the specific case, that for all group members $\beta$ is 0 or 1, a complete classification of equilibria can be obtained; for an example, see Fig. 2.2.

**Theorem 2 (Equilibria when all $\beta$’s are equal to 0 or 1)**

Suppose all $w_{SR}$ are nonzero and for all $C$ it holds $\beta_C = 0$ or $\beta_C = 1$, in other words, the whole group $G$ is partitioned into the two subsets

$S_0 = \{ A \in G \mid \beta_A = 0 \}$ \hspace{1cm} $S_1 = \{ B \in G \mid \beta_B = 1 \}$

Then for an equilibrium the following holds:

(a) If $S_0 = G$ and $S_1 = \emptyset$, i.e., $\beta_C = 0$ for all $C$, then

either $q_C = 0$ for all $C$ (attracting) or $q_C = 1$ for all $C$ (non-attracting).

(b) If $S_1 = G$ and $S_0 = \emptyset$, i.e., $\beta_C = 1$ for all $C$, then
either $q_C = 0$ for all $C$ (non-attracting) or $q_C = 1$ for all $C$ (attracting).

(c) If $\#(S_0) = \#(S_1) = 1$, i.e., there is exactly one member $A$ with $\beta_A = 0$, and exactly one member $B$ with $\beta_B = 1$, then there are two possibilities:

(i) $q_A = 0$ for $A \in S_0$ and $q_B$ has any value for $B \in S_1$

(ii) $q_B = 1$ for $B \in S_1$ and $q_A$ has any value for $A \in S_0$

(d) If $\#(S_0) = 1$ and $\#(S_1) \geq 2$, i.e., there is exactly one member $A$ with $\beta_A = 0$, and there are at least two members $B_1$ and $B_2$ with $\beta_{B_1} = \beta_{B_2} = 1$, then there are two possibilities:

(i) $q_C = 0$ for all $C \in G$

(ii) $q_B = 1$ for all $B \in S_1$ and $q_A$ has any value for $A \in S_0$

(e) If $\#(S_1) = 1$, and $\#(S_0) \geq 2$, i.e., there is exactly one member $B$ with $\beta_B = 1$, and there are at least two members $A_1$ and $A_2$ with $\beta_{A_1} = \beta_{A_2} = 0$, then there are two possibilities:

(i) $q_C = 1$ for all $C \in G$

(ii) $q_A = 0$ for all $A \in S_0$ and $q_B$ has any value for $B \in S_1$

(f) If $\#(S_0) \geq 2$ and $\#(S_1) \geq 2$, i.e., there are at least two members $A_1$ and $A_2$ with $\beta_{A_1} = \beta_{A_2} = 0$ and also at least two members $B_1$ and $B_2$ with $\beta_{B_1} = \beta_{B_2} = 1$, then there are three possibilities:

(i) $q_c = 0$ for all $C \in G$

(ii) $q_c = 1$ for all $C \in G$

(iii) $q_A = 0$ for all $A \in S_0$ and $q_B = 1$ for all $B \in S_1$

For the specific case of three group members, where one member has $\beta$ is 0, one has 1 and one has neither, the following holds; for an example, see Fig. 2.3.

**Proposition 3 (A case for 3 members)**

Consider a group $G$ which consists of three members named by $a$, $b$, $c$ with $\beta_a = 0$, $\beta_b = 1$, and $\beta_c = \beta$, where $0 < \beta < 1$ is assumed. Moreover, suppose all $w_{SR}$ are nonzero. Then the following are the possibilities for equilibria:

(i) $q_a = q_b = q_c = 0$

(ii) $q_a = q_b = q_c = 1$

(iii) $q_a = 0$, $q_b = 1$ and $q_c = \beta w_{bc} / ( (1-\beta)w_{ac} + \beta w_{bc})$

In particular, when $w_{ac} = w_{bc}$, then the value for $q_c$ in (iii) is $\beta$.

The following proposition shows that only in trivial cases a group member with $\beta$ not 0 or 1 can reach 0 or 1.

**Proposition 4 ($q_A = 0$ with $\beta_A > 0$ or $q_B = 1$ with $\beta_B < 1$)**

Suppose all $w_{SR}$ are nonzero. Then for an equilibrium it holds

(i) If $q_A = 0$ for some $A$ with $\beta_A > 0$ then $q_C = 0$ for all $C \in G$.

(ii) If $q_B = 1$ for some $B$ with $\beta_B < 1$ then $q_C = 1$ for all $C \in G$. 

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The case that all group member converge to an equal equilibrium value, which is not 0 or 1, only occurs when all $\beta$s are 0.5; for an example, see Fig. 2.4.

**Theorem 3 (Equal equilibrium values for all members)**  
Suppose all $w_{SR}$ are nonzero, then for an equilibrium the following are equivalent:

(i) For some $q$ with $0 < q < 1$ it holds $q_C = q$ for all $C$.

(ii) For all $C$ it holds $\beta_C = 0.5$.

For the case of two persons, a complete classification can be found, as shown in the following theorem.

**Theorem 4 (The case of two persons)**  
Suppose the group consists of two persons named by $a$ and $b$. Then for an equilibrium, there are the following possibilities:

(i) When $\beta_a + \beta_b \neq 1$ the only two possibilities are:

- $q_a = q_b = 0$ attracting when $\beta_a + \beta_b < 1$
- $q_a = q_b = 1$ attracting when $\beta_a + \beta_b > 1$

(ii) When $\beta_a + \beta_b = 1$ attracting equilibria occur where $q_a$ and $q_b$ get values between 0 and 1.

### 2.6 Formal Verification of the Emotion Contagion Spiral Model

In this section, it is discussed how traces generated by the emotion contagion models have been formally verified. The temporal predicate logical language TTL [6] used to express properties to be verified supports formal specification and analysis of dynamic properties, covering both qualitative and quantitative aspects. TTL is built on atoms referring to states of the world, time points and traces, i.e., trajectories of states over time. In addition, dynamic properties are (sorted) temporal predicate logic statements that can be formulated with respect to traces based on the state ontology Ont in the following manner.

Given a trace $\gamma$ over state ontology Ont, the state in $\gamma$ at time point $t$ is denoted by $\text{state}(\gamma, t)$. These states can be related to state properties via the formally defined satisfaction relation denoted by the infix predicate $\models$: $\text{state}(\gamma, t) \models p$ denotes that state property $p$ holds in trace $\gamma$ at time $t$. Based on these statements, dynamic properties can be formulated in a formal manner in a sorted predicate logic, using quantifiers over time and traces and the usual logical connectives such as $\neg$, $\land$, $\lor$, $\Rightarrow$, $\forall$, $\exists$. A dedicated software environment has been developed for TTL, featuring both a Property Editor for building and editing TTL properties and a Checking Tool that enables
automated formal verification of such properties against a set of (simulated or empirical) traces.

The purpose of the type of verification performed here is to check whether the model behaves as it should. A typical example of a property that may be checked is whether no unexpected situations occur, such as a variable running out of its bounds (e.g., $q_A(t) > 1$, for some $t$ and $A$), or whether eventually, an equilibrium value is reached. Other more complex examples can be found in the theorems presented in the previous section. For the emotion contagion model, a number of such dynamic properties have been formalized in TTL varying from properties addressing limit behavior (equilibria reached) to properties of the process from initial values to the equilibria. Below, a number of these properties are introduced, both in semi-formal and in informal notation (where state($\gamma$, $t$) $\models p$ denotes that $p$ holds in trace $\gamma$ at time $t$). Note that the properties are all defined for a particular trace $\gamma$ and sometimes for a particular time interval between $tb$ and $te$.

**P1a - Emotional Stability for Agent a**
For all time points $t_1$ and $t_2$ between $tb$ and $te$ in trace $\gamma$, if at $t_1$ the level of emotion of agent $a$ is $x_1$, then at $t_2$ the level of emotion of agent $a$ is between $x_1 - \alpha$ and $x_1 + \alpha$.

$P1a(\gamma:TRACE, tb, te:TIME, a:AGENT, \alpha:REAL) \equiv$
$\forall t_1, t_2:TIME \forall x_1, x_2:REAL$
$\text{state}(\gamma, t_1) \models \text{emotion(agent(a), } x_1) \&$
$\text{state}(\gamma, t_2) \models \text{emotion(agent(a), } x_2) \&$
$tb \leq t_1 \leq te \& tb \leq t_2 \leq te \Rightarrow x_1 - \alpha \leq x_2 \leq x_1 + \alpha$

This property can be used to verify in which situations a certain agent’s level of emotion does not fluctuate much. It has been found, for example, that for the trace shown in Figure 2.3 and for $\alpha = 0.00001$, the emotion of agent $a$ remains stable between time point 28 and 50. In other words, checking $P1a(\text{traceFig2, 28, 50, a, 0.00001})$ was successful, where traceFig2 is a trace of Figure 2.3.

**P1b - Emotional Stability for Agent a around Value x**
For all time points $t$ between $tb$ and $te$ in trace $\gamma$
the level of emotion of agent $a$ is between $x - \alpha$ and $x + \alpha$ (where $\alpha$ is a constant).

$P1b(\gamma:TRACE, tb, te:TIME, x:REAL, a:AGENT, \alpha:REAL) \equiv$
$\forall t:TIME \forall y:REAL$
$\text{state}(\gamma, t) \models \text{emotion(agent(a), } y) \&$
$tb \leq t \leq te \Rightarrow x - \alpha \leq y \leq x + \alpha$

As a variant of P1a, property P1b can be used to check whether an agent’s level of emotion stays around a certain (given) value. For example, for $\alpha =$
0.0001, property P1b(traceFig2, 25, 50, 0.4333, b, 0.0001) was true. One step further, P1a and P1b can be used as building blocks to check the propositions and theorems related to equilibria presented in the previous section against the generated traces. For example, property P1c checks whether Theorem 3 holds:

**P1c - Equal Equilibria**

If for all agents $A$ and $B$, $\gamma_{AB}$ is nonzero in trace $\gamma$ then eventually the same equilibrium $q$ (between 0 and 1) will occur for all agents.

$$P1c(\gamma: \text{TRACE}, \alpha: \text{REAL}) \equiv [\forall a1,a2: \text{AGENT} \ [a1 \neq a2 \Rightarrow \exists g: \text{REAL}>0 \ [\text{state}(\gamma, 1) \models \text{has}_\gamma(a1,a2,g)]]] \Rightarrow [\exists q: \text{REAL} \ \forall a: \text{AGENT} \ P1b(\gamma,40,50,q,a, \alpha)]$$

This property, which has been proven in the mathematical analysis, has been checked for $\alpha = 0.07$ for all generated traces, and indeed was confirmed. In addition, similar properties have been formulated that make claims about the equilibria on the basis of the initial settings. Details of these properties are not shown here. However, some examples (in informal notation) are:

- In case $\gamma_{sr} = 0$ for all agents, then each agent ends up in an equilibrium that is equal to its initial emotion value.
- In case $\delta_r = 0$ for exactly 1 agent $A$ (i.e., $\delta_A = 0$), and other $\delta_r$ are nonzero, and all $\alpha_{sr}$ and $\varepsilon_s$ are nonzero for all agents, then each agent ends up in an equilibrium that is equal to the initial emotion value of agent A.
- In case $\delta_r = 0$ and $\varepsilon_i = 0$ for exactly 1 agent $A$ (i.e., $\delta_A = \varepsilon_A = 0$), and other $\delta_r$ and $\varepsilon_i$ are nonzero, and all $\alpha_{sr}$ are nonzero for all agents, then agent A ends up in an equilibrium that is equal to its initial emotion value, and all other agents end up in an equilibrium that is in between their initial emotion values.
- In case $\delta_r = 0$ for exactly 2 agents A and B (i.e., $\delta_A = \delta_B = 0$), and other $\delta_r$ are nonzero, and all $\alpha_{sr}$ and $\varepsilon_s$ are nonzero for all agents, then agent A and B end up in an equilibrium that is equal to their initial emotion value, and all other agents end up in an equilibrium that is in between the initial emotion values of A and B.
**P2a - Monotonic Increase of Emotion**

For all time points $t_1$ and $t_2$ between $t_b$ and $t_e$ in trace $\gamma$, if at $t_1$ the level of emotion of agent $a$ is $x_1$, and at $t_2$ the level of emotion of agent $a$ is $x_2$ and $t_1 < t_2$, then $x_1 \leq x_2$.

$$P2a(\gamma; \text{TRACE, } t_b, t_e; \text{TIME, } a; \text{AGENT}) =$$

$$\forall t_1, t_2; \text{TIME} \forall x_1, x_2; \text{REAL}$$

$$\text{state}(\gamma, t_1) \models \text{emotion(agent}(a), x_1) \&$$

$$\text{state}(\gamma, t_2) \models \text{emotion(agent}(a), x_2) \&$$

$$t_b \leq t_1 \leq t_e \& t_b \leq t_2 \leq t_e \& t_1 < t_2 \Rightarrow x_1 \leq x_2$$

Property P2a and the variant P2b addressing monotonic decrease (by replacing $\leq$ in the consequent by $\geq$) can be used to check whether an agent’s level of emotion increases or decreases monotonically over a certain interval. Such monotonicity, for example, occurs for agent $c$ during the whole trace shown in Figure 2.3 (i.e., property P2b(traceFig2, 1, 50, c) succeeded). Furthermore, these properties can be used as building blocks to check the propositions and theorems related to monotonicity presented in the previous section against the generated traces. For example, property P2c checks whether part (c) and (d) of Proposition 1 hold:

**P2c - Conditional Monotonicity**

For all agents $A$, if $q_A^* \geq q_A$ between $t_b$ and $t_e$ in trace $\gamma$, then $q_A$ is monotonically increasing during this interval, and if $q_A^* \leq q_A$ between $t_b$ and $t_e$ in trace $\gamma$, then $q_A$ is monotonically decreasing during this interval.

$$P2c(\gamma; \text{TRACE, } t_b, t_e; \text{TIME}) =$$

$$\forall a; \text{AGENT}$$

$$[[ \forall t; \text{TIME} \exists a_2, a_3; \text{AGENT} \exists x_1, x_2, x_3, w_2, w_3; \text{REAL}$$

$$\text{state}(\gamma, t) \models \text{emotion(agent}(a_1), x_1) \&$$

$$\text{state}(\gamma, t) \models \text{emotion(agent}(a_2), x_2) \&$$

$$\text{state}(\gamma, t) \models \text{emotion(agent}(a_3), x_3) \& a_2 \neq a_3 \& t_b \leq t \leq t_e \&$$

$$\text{state}(\gamma, 1) \models \text{has}_w\text{for(agent}(a_2), agent(a_1), w_2) \&$$

$$\text{state}(\gamma, 1) \models \text{has}_w\text{for(agent}(a_3), agent(a_1), w_3) \&$$

$$w_2 \cdot x_2 + w_3 \cdot x_3 \geq w_1] \Rightarrow p2a(\gamma, t_b, t_e, a_1)] \&$$

$$[[ \forall t; \text{TIME} \exists a_2, a_3; \text{AGENT} \exists x_1, x_2, x_3, w_2, w_3; \text{REAL}$$

$$\text{state}(\gamma, t) \models \text{emotion(agent}(a_1), x_1) \&$$

$$\text{state}(\gamma, t) \models \text{emotion(agent}(a_2), x_2) \&$$

$$\text{state}(\gamma, t) \models \text{emotion(agent}(a_3), x_3) \& a_2 \neq a_3 \& t_b \leq t \leq t_e \&$$

$$\text{state}(\gamma, 1) \models \text{has}_w\text{for(agent}(a_2), agent(a_1), w_2) \&$$

$$\text{state}(\gamma, 1) \models \text{has}_w\text{for(agent}(a_3), agent(a_1), w_3) \&$$

$$w_2 \cdot x_2 + w_3 \cdot x_3 \leq w_1] \Rightarrow p2b(\gamma, t_b, t_e, a_1)]$$

---

1 A strict variant of such properties can be created by replacing $\leq$ by $<$.  

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Here, $q_{a,t}$ is explained in the section after the introduction section. This property has been confirmed for all possible intervals in all generated traces.

**P3 - Emotion between Boundaries**

For all time points $t$ between $t_b$ and $t_e$ in trace $\gamma$

if at $t$ the level of emotion of agent $a$ is $x$, then $\min < x < \max$.

$P3(\gamma \colon \text{TRACE}, t_b, t_e \colon \text{TIME}, \max, \min \colon \text{REAL}, a \colon \text{AGENT}) \equiv$

$\forall t \colon \text{TIME} \ \forall x \colon \text{REAL}$

$\text{state}(\gamma, t) \models \text{emotion}(agent(a), x) \land t_b \leq t \leq t_e \Rightarrow \min \leq x \leq \max$

This property can be used to check whether the emotion of an agent stays between certain boundaries. For example, no emotional value should ever become lower than 0 or higher than 1. This turned out to be the case for all generated traces where $\Delta t \leq 1/(\#(G) - 1)$. That is, property $P3(\text{trace}, 1, 50, 0.0, 1.0, X)$ succeeded for all traces trace with these settings and agents $X$, which confirms Theorem 5 of the previous section. In addition, it was found that the property failed for some traces that do not have these settings. E.g., for a trace with $\Delta t = 0.7$, all $\gamma_{SR} = 1$, and initial values $q_A = 0.3$, $q_B = 0.1$, and $q_C = 0.9$, the emotion values eventually run out of their boundaries.

**P4 - Emotion Agent $a_1$ above Agent $a_2$**

For all time points $t$ between $t_b$ and $t_e$ in trace $\gamma$, if at $t$ the level of emotion of agent $a_1$ is $x_1$ and the level of emotion of agent $a_2$ is $x_2$, then $x_1 \geq x_2$.

$P4(\gamma \colon \text{TRACE}, t_b, t_e \colon \text{TIME}, a_1, a_2 \colon \text{AGENT}) \equiv$

$\forall t \colon \text{TIME} \ \forall x_1, x_2 \colon \text{REAL}$

$\text{state}(\gamma, t) \models \text{emotion}(agent(a_1), x_1) \land \text{state}(\gamma, t) \models \text{emotion}(agent(a_2), x_2) \land t_b \leq t \leq t_e \Rightarrow x_1 \geq x_2$

Property $P4$ can be used to check whether an agent’s emotion level stays above (or below) another agent’s level during a specified interval. For example, in the trace of Figure 2.3, agent $c$ always has a higher emotion than agent $a$ (i.e., property $P4(\text{traceFig2}, 1, 50, c, a)$ succeeded). However, in the end the difference becomes very small, and if the simulation were continued longer, eventually this property would fail.

**P5 - Emotion Approaches Value $x$ with Speed $s$**

For all time points $t_1$ and $t_2$ between $t_b$ and $t_e$ in trace $\gamma$, if at $t_1$ the level of emotion of agent $a$ is $x_1$, and at $t_2$ the level of emotion of agent $a$ is $x_2$, and $t_2 = t_1 + 1$, then $s \cdot |x - x_1| \geq |x - x_2|$ (here $s$ is a constant $< 1$).

$P5(\gamma \colon \text{TRACE}, t_b, t_e \colon \text{TIME}, x \colon \text{REAL}, a \colon \text{AGENT}) \equiv$

$\forall t_1, t_2 \colon \text{TIME} \ \forall x_1, x_2 \colon \text{REAL}$

$\text{state}(\gamma, t_1) \models \text{emotion}(agent(a), x_1) \land \text{state}(\gamma, t_2) \models \text{emotion}(agent(a), x_2) \land t_b \leq t_1 \leq t_e \land t_b \leq t_2 \leq t_e \land t_2 = t_1 + 1 \Rightarrow |x - x_1| \cdot s \geq |x - x_2|$
Property P5 can be used to check whether an agent’s emotion level approaches a given value $x$, and to determine the speed $s$ with which this happens (where $0 < s < 1$, and a high $s$ denotes a slow speed). For example, for the trace shown in Figure 2.4, it turned out that agent $b$ approaches emotion level 0.3 with a speed of approximately 0.9991.

**P6 - Higher Beta’s lead to Higher Emotion Levels**

If for all agents the initial level of emotion is higher (or equal) in trace $\gamma_1$ than in $\gamma_2$

and for all agents the beta is higher (or equal) in trace $\gamma_1$ than in $\gamma_2$

then for all agents the final level of emotion will be higher (or equal) in trace $\gamma_1$ than in $\gamma_2$.

$$
P6(\gamma_1, \gamma_2; \text{TRACE}, \text{tb}, \text{te}; \text{TIME}) \equiv 
\forall a: \text{AGENT} \exists x_1, x_2: \text{REAL} 
\text{state}(\gamma_1, \text{tb}) \models \text{emotion}(agent(a), x_1) \& \text{state}(\gamma_2, \text{tb}) \models \text{emotion}(agent(a), x_2) \& x_1 \geq x_2 \] 
\& 
\forall a: \text{AGENT} \exists x_1, x_2: \text{REAL} 
\text{state}(\gamma_1, \text{tb}) \models \text{has_beta}(agent(a), x_1) \& \text{state}(\gamma_2, \text{tb}) \models \text{has_beta}(agent(a), x_2) \& x_1 \geq x_2 \] 
\Rightarrow 
\forall a: \text{AGENT} \exists x_1, x_2: \text{REAL} 
\text{state}(\gamma_1, \text{te}) \models \text{emotion}(agent(a), x_1) \& \text{state}(\gamma_2, \text{te}) \models \text{emotion}(agent(a), x_2) \& x_1 \geq x_2 
$$

This property can be used to compare traces with different parameter settings. It turned out to hold for all generated traces, as long as the initial values were not 0 or 1.

2.7 The Ambient Agent Model for Group Emotion Analysis

The emotion contagion model described in Section 2.3 above can be used by an ambient agent to analyse the past, present and future (expected) dynamics of a team’s emotion contagion processes. The main goal of the ambient agent designed is to estimate and predict the level of a given type of emotion in the group at present and future points in time and based on such an analysis propose actions whenever considered needed. The emotion considered is assumed to be a positive emotion, so when the emotion level of the group is expected to become too low, this analysis process should detect this early enough to intervene.

Concepts needed in such a model for an ambient agent concern the ambient agent’s estimations of the relevant human’s states at different points in time; these estimations are described by the ambient agent’s observations and beliefs; in addition an assessment of the (expected) group’s emotion state is needed. An assessment is generated when the group emotion level at some (future) time point is expected to be too low, compared to a certain norm ($EN$).
Moreover, to model direct observation of individual emotion levels, the concept *expressed emotion level* \( (\varepsilon, q_A) \) is used, as the emotion level that can be observed from someone’s face, for example, by use of a face reader. This may differ from the emotion level in that the expressiveness factor has also effect on it.

Table 2.2: Concepts to reason about emotion contagion and their formalization

<table>
<thead>
<tr>
<th>Concept</th>
<th>Formalisation</th>
</tr>
</thead>
<tbody>
<tr>
<td>observation that person ( A ) has expressed emotion level ( EV ) at time ( T )</td>
<td>observed(agent, has_expressed_emotion_level_at(A:AGENT, EV:REAL, T:REAL))</td>
</tr>
<tr>
<td>belief that person ( A ) has expressed emotion level ( EV ) at time ( T )</td>
<td>belief(agent, has_expressed_emotion_level_at(A:AGENT, EV:REAL, T:REAL))</td>
</tr>
<tr>
<td>belief that person ( B ) has expressiveness ( E )</td>
<td>belief(agent, has_expressiveness(B:AGENT, E:REAL))</td>
</tr>
<tr>
<td>belief that person ( A ) has openness for received emotion ( D )</td>
<td>belief(agent, has_openness(A:AGENT, D:REAL))</td>
</tr>
<tr>
<td>belief that the channel from ( B ) to ( A ) has strength ( C )</td>
<td>belief(agent, has_channel_strength(B:AGENT, A:AGENT, C:REAL))</td>
</tr>
<tr>
<td>belief that the contagion strength from ( B ) to ( A ) is ( C_S )</td>
<td>belief(agent, has_contagion_strength(B:AGENT, A:AGENT, C_S:REAL))</td>
</tr>
<tr>
<td>belief that the overall contagion strength to receiver ( A ) is ( C_S )</td>
<td>belief(agent, has_overall_contagion_strength(A:AGENT, C_S:REAL))</td>
</tr>
<tr>
<td>belief that step size is ( DT )</td>
<td>belief(agent, stepsize(DT:REAL))</td>
</tr>
<tr>
<td>belief that person ( A ) has relevance ( R )</td>
<td>belief(agent, has_relevance(A:AGENT, R:REAL))</td>
</tr>
<tr>
<td>belief that person ( A ) has emotion level ( V ) at time ( T )</td>
<td>belief(agent, has_emotion_level_at(A:AGENT, V:REAL, T:REAL))</td>
</tr>
<tr>
<td>belief that the group emotion level at ( T ) is ( GE )</td>
<td>belief(agent, group_emotion_level_at(GE:REAL, T:REAL))</td>
</tr>
<tr>
<td>belief that the group emotion norm is ( EN )</td>
<td>belief(agent, group_emotion_norm(EN:REAL))</td>
</tr>
<tr>
<td>assessment that the deficient of the group emotion at ( T ) is ( ED )</td>
<td>assessment(agent, group_emotion_deficient_at(ED:REAL, T:REAL))</td>
</tr>
</tbody>
</table>

To formalize the concepts introduced in this and the previous sections, a number of logical atoms are introduced that incorporate numerical representations; see Table 2.2. Note that in order to generate and analyze possible temporal patterns for the future, some of the atoms have an additional
time variable \( T \). This is used to make predictions about future emotion states, as part of the analysis.

The dynamic relationships of the model to reason about emotion contagion are described and formalised as follows. Note that the beliefs on emotion expressiveness, openness, and channel strengths are assumed to be initially given and to persist (until they are changed). Moreover, a scenario is considered where at some (initial) point in time the current emotion levels of the members are estimated or observed, and from that time point onwards, the beliefs on emotion levels for subsequent time points are determined, as a form of temporal projection (or prediction).

First the role of observed expressed emotions is formalised. The agent is assumed to possess observation equipment in the form of a face reader with software that detects emotion expressions from face images. This expressed emotion \( EV \) results from the emotion level \( V \) and the expressiveness \( E \) by which the emotion is displayed on the face. In the model it is assumed that the expressed emotion level is formalised as the product \( V \times E \). Note that this means that it is assumed that the expressiveness (being a number between 0 and 1) always reduces the level of the emotion: \( EV \leq E \).

In other words, this assumption excludes the situation that an emotion level is expressed that is not there (no faking of emotions). Moreover, note that in ADR2 (Analysis Dynamic Rule 2) below it is assumed that the expressiveness factor \( E \) is nonzero. Then under the assumptions discussed above, from an expressed emotion level \( EV \) the emotion level \( V \) itself can be determined as \( V = EV/E \).

**ADR1 Observing group members’ expressed emotion levels**
If the agent observes an expressed emotion level then the ambient agent will believe this.
\[
\text{observes(agent, has_expressed_emotion_level_at(A, V, T))} \rightarrow \text{belief(agent, has_expressed_emotion_level_at(A, V, T))}
\]

**ADR2 Generating a belief on an emotion level from a belief on an expressed emotion level**
If the agent believes that a group member has expressed emotion level \( EV \) and that this group member has expressiveness \( E \) then it will generate a belief that this group member has emotion level \( EV/E \).
\[
\text{belief(agent, has_expressed_emotion_level_at(A, EV, T))} \& \text{belief(agent, has_expressiveness(E))} \rightarrow \text{belief(agent, has_emotion_level_at(A, EV/E, T))}
\]

**ADR3 Generating beliefs on contagion strengths**
If the ambient agent believes that \( B \) has expressiveness \( E \) and the ambient agent believes that the channel from \( B \) to \( A \) has strength \( C \)
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and the ambient agent believes that \( A \) has openness \( D \)
then the ambient agent will believe that the contagion strength from \( B \) to \( A \) will be \( E \cdot C \cdot D \)

\[
\text{belief(agent, has_expressiveness(B, E))} \land \\
\text{belief(agent, has_channel_strength(B, A, C))} \land \\
\text{belief(agent, has_openness(A, D))} \\
\rightarrow \text{belief(agent, has_contagion_strength(B, A, E \cdot C \cdot D))}
\]

ADR4 Updating beliefs on emotion levels
If \( A \neq B \) and \( B \neq C \) and \( C \neq A \)
and the ambient agent believes that \( B \) has emotion level \( V_2 \) at time \( T \)
and the ambient agent believes that \( C \) has emotion level \( V_3 \) at time \( T \)
and the ambient agent believes that the contagion strength from \( B \) to \( A \) is \( C_S2 \)
and the ambient agent believes that the contagion strength from \( C \) to \( A \) is \( C_S3 \)
and \( Q_1 = (C_S2 \cdot V_2 + C_S3 \cdot V_3) / (C_S2 + C_S3) \)
and the ambient agent believes that \( A \) has emotion level \( V_1 \) at time \( T \)
and the ambient agent believes that \( A \) has beta \( B_{E1} \)
and the ambient agent believes that \( A \) has eta \( E_{TA1} \)
and the ambient agent believes that \( A \) has gamma \( G_1 \)
and the ambient agent believes that the step size is \( DT \)
then the ambient agent will believe that the emotion level of \( A \) will be

\[
G_1 \cdot E_{TA1} \cdot B_{E1} \cdot (1 - (1-Q_1) \cdot (1-V_1)) + (1-B_{E1}) \cdot Q_1 \cdot V_1 + (1-E_{TA1}) \cdot Q_1 - V_1 \cdot DT
\]

\[
A \neq B \land B \neq C \land C \neq A \land \\
\text{belief(agent, has_emotion_level_at(B, V_2, T))} \land \\
\text{belief(agent, has_emotion_level_at(C, V_3, T))} \land \\
\text{belief(agent, has_contagion_strength(B, A, C_S2))} \land \\
\text{belief(agent, has_contagion_strength(C, A, C_S3))} \land \\
Q_1 = (C_S2 \cdot V_2 + C_S3 \cdot V_3) / (C_S2 + C_S3) \\
\text{belief(agent, has_emotion_level_at(A, V_1, T))} \land \\
\text{belief(agent, has_beta(A, B_{E1}))} \land \\
\text{belief(agent, has_eta(A, E_{TA1}))} \land \\
\text{belief(agent, has_gamma(A, G_1))} \land \\
\text{belief(agent, step_size(DT))} \\
\rightarrow \text{belief(agent, has_emotion_level_at(A, V_1 + G_1 \cdot [E_{TA1} \cdot B_{E1} \cdot (1 - (1-Q_1) \cdot (1-V_1)) + (1-B_{E1}) \cdot Q_1 \cdot V_1 + (1-E_{TA1}) \cdot Q_1 - V_1] \cdot DT, T+DT))}
\]

An analysis also involves an assessment of the (expected) level of the group’s emotion. To this end, first a belief on the group’s emotion level is generated.

ADR5 Determining beliefs on the group’s emotion level
If the ambient agent believes that the group members have emotion levels \( V_1, V_2, V_3 \)
and relevance \( R_1, R_2, R_3 \) respectively
then it will believe that the group’s emotion level is \( R_1 \cdot V_1 + R_2 \cdot V_2 + R_3 \cdot V_3 \).

\[
\text{belief(agent, has_emotion_level_at(a_1, V_1, T))} \land \\
\text{belief(agent, has_emotion_level_at(a_2, V_2, T))} \land \\
\text{belief(agent, has_emotion_level_at(a_3, V_3, T))} \land \\
\text{belief(agent, has_relevance(a_1, R_1))} \land \\
\text{belief(agent, has_relevance(a_2, R_2))} \\
\rightarrow \text{belief(agent, has_emotion_level_at(A, V_1 + G_1 \cdot [E_{TA1} \cdot B_{E1} \cdot (1 - (1-Q_1) \cdot (1-V_1)) + (1-B_{E1}) \cdot Q_1 \cdot V_1 + (1-E_{TA1}) \cdot Q_1 - V_1] \cdot DT, T+DT))}
\]
belief(agent, has_relevance(a3, R3))

→ belief(agent, group_emotion_level_at(R1*V1+ R2*V2+R3*V3, T))

An assessment is generated when the group emotion level at some (future) time point is expected to be too low, compared to a certain norm. In case of a negative outcome further action may be needed, to avoid this undesired situation. The assessment includes an estimation of how much the group emotion level is too low (the group emotion deficient):

ADR6 Assessment of the group’s emotion level
If the ambient agent believes that the group emotion level $V$ at time $T$ is lower than the emotion norm $EN$, then it will assess the situation as having a group emotion deficient $EN-V$ at $T$.

belief(agent, group_emotion_level_at(V, T)) &
belief(agent, group_emotion_norm(EN)) & V<EN

→ assessment(agent, group_emotion_deficient_at(EN-V, T))

2.8 The Agent Model for Group Emotion Support
In the previous sections, the emotion contagion model and the analysis process based on it have been discussed. In this section, the support model is introduced that uses these models to provide intelligent support to humans in cases where the group emotion level is expected to become below a certain norm. The support model introduced here, uses a heuristic approach. The idea is that an ambient agent will reason about the proper actions that should be undertaken by the team leader to keep the group emotion level optimal. For example, it uses knowledge expressing that in case the group emotion level (e.g., relaxedness or happiness) is lower than a certain norm, certain members are to be detected that play a crucial role in a negative or positive sense and give them either a pep talk to or to increase or decrease their impact on the other group members.

When a negative assessment of the (future) group emotion state is made, then the ambient agent is assumed to propose actions to the team leader, in order to avoid such states. Some examples of possible actions are:

- giving a group member that negatively affects the emotion in the team a less central role (decreasing the emotion contagion strengths from this person)
- ask a person with a positive emotion level (for example the team leader) either to not be too open for other members (decrease the person’s openness; i.e., $\delta_R$) or to be more expressive (increase the person’s expressiveness; i.e., $\varepsilon_S$)
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Two heuristics that are applied are the following:

- **let the group members with lower emotion levels get less impact on the other members, and get more impact from the other members**
- **let the group members with higher emotion levels get more impact on the other members, and get less impact from the other members**

Here ‘higher’ and ‘lower’ can be defined as the members with highest or lowest emotion level, but also as above or under the group’s emotion level. In general, two (low and high) emotion thresholds are assumed for this, where a specific case is that these thresholds are both equal to the group’s emotion level.

For a group member under the low threshold, his or her impact on the other members can be decreased by (encouragement for) decreasing the person’s expressiveness, or by decreasing the channel strengths from this person to the other members. Moreover, the person’s impact from other members can be increased by increasing the person’s openness, and by increasing the channel strengths from the other members. For an overview of the action options based on the two heuristics, see Table 2.2.

<table>
<thead>
<tr>
<th></th>
<th>person under low threshold</th>
<th>person above high threshold</th>
</tr>
</thead>
<tbody>
<tr>
<td>expressiveness</td>
<td>decrease</td>
<td>increase</td>
</tr>
<tr>
<td>openness</td>
<td>increase</td>
<td>decrease</td>
</tr>
<tr>
<td>channels to others</td>
<td>decrease</td>
<td>increase</td>
</tr>
<tr>
<td>channels from others</td>
<td>increase</td>
<td>decrease</td>
</tr>
</tbody>
</table>

This approach does not give indications for the adjustment extent to which such increase or decrease has to be applied. When such adjustment extents are chosen, the approach can also be combined with a feasibility ranking approach described next.

After the ambient agent generates the actions options, they have to be ranked on their (in)feasibility, expressing how difficult they are to achieve, because it may happen that some action options can be easily realized whereas others are difficult to realize. The action option with the lowest infeasibility will be chosen and proposed by the ambient agent to the team leader. A realistic ranking, from the most to the least infeasible parameter, could be:

1) openness ($\delta_A$), because it seems that this personality characteristic is difficult to change overtime;
2) expressiveness ($\varepsilon_A$) because this personality characteristic can be ‘faked’ (one can display emotions that are not experienced);
3) channel strength ($\alpha_{BA}$) because it is easy to lower the channel strength’s between a person and every other group member, by simply separating this individual from the group.

The formalization of the concepts is given in Table 2.3. For example, the concept that an agent has a belief about that the low threshold for an individual emotion is a certain real number, is formalised as: belief(agent, low_threshold(LT:REAL)). The formalization of the dynamic relationships is stated below. For example, Support Dynamic Rule 1, SDR1, states that if the ambient agent has a belief that person $A$ has an emotional value $V$ that is lower than threshold $LT$, then the ambient agent believes that person $A$ is a low emotion member.

**SDR1 Low emotion member identification**

If the ambient agent believes that $A$ has emotion level $V$ at $T0$ and that the low threshold is $LT$ then the agent will believe that $A$ is a low emotion member

belief(agent, has_emotion_level_at(A, V, T0)) & belief(agent, low_threshold(LT)) & $V\leq LT$ 

$\rightarrow$ belief(agent, low_emotion_member(A))

**SDR2 High emotion member identification**

If the ambient agent believes that $A$ has emotion level $V$ at $T0$ and that the high threshold is $HT$ then the agent will believe that $A$ is a high emotion member

belief(agent, has_emotion_level_at(A, V, T0)) & belief(agent, high_threshold(HT)) & $V\geq HT$ 

$\rightarrow$ belief(agent, high_emotion_member(A))

**SDR3 Heuristic generation of expressiveness action options for low emotion members**

If the ambient agent believes that $A$ is a low emotion member and a group emotion deficient $ED$ at $T$ was identified and it believes that the adjustment extent is $AE$ and the expressiveness of $A$ is $E$ then the agent will believe that an action option is to change the value $E$ for expressiveness to $E - AE*ED*E$

belief(agent, low_emotion_member(A)) & assessment(agent, group_emotion_deficient_at(ED, T)) & belief(agent, adjustment_extent(AE)) & belief(agent, has_expressiveness(A, E)) 

$\rightarrow$ belief(agent, action_option(adjust_to(expressiveness(A), E, $E - AE*ED*E$)))
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Table 2.3: Formalization of concepts in the support model

<table>
<thead>
<tr>
<th>Concept</th>
<th>Formalisation</th>
</tr>
</thead>
<tbody>
<tr>
<td>the agent believes that the low threshold for individual emotion levels is $LT$</td>
<td>belief(agent, \text{low_threshold}(LT:REAL))</td>
</tr>
<tr>
<td>the agent believes that the high threshold for individual emotion levels is $HT$</td>
<td>belief(agent, \text{high_threshold}(HT:REAL))</td>
</tr>
<tr>
<td>the agent believes that $A$ is a low emotion member</td>
<td>belief(agent, \text{low_emotion_member}(A:AGENT))</td>
</tr>
<tr>
<td>the agent believes that $A$ is a high emotion member</td>
<td>belief(agent, \text{high_emotion_member}(A:AGENT))</td>
</tr>
<tr>
<td>the agent believes that the adjustment extent is $AE$</td>
<td>belief(agent, \text{adjustment_extent}(AE:REAL))</td>
</tr>
<tr>
<td>the agent believes that an action option is to change the value $W_1$ for expressiveness of $A$ to $W_2$</td>
<td>belief(agent, \text{action_option}(adjust_to(expressiveness(A:AGENT), W_1:REAL, W_2:REAL)))</td>
</tr>
<tr>
<td>the agent believes that an action option is to change the value $W_1$ for channel strength from $A$ to $B$ to $W_2$</td>
<td>belief(agent, \text{action_option}(adjust_to(channel_strength(A:AGENT, B:AGENT), W_1:REAL, W_2:REAL)))</td>
</tr>
<tr>
<td>the agent believes that an action option is to change the value $W_1$ for openness of $A$ to $W_2$</td>
<td>belief(agent, \text{action_option}(adjust_to(openness(A:AGENT), W_1:REAL, W_2:REAL)))</td>
</tr>
<tr>
<td>The agent believes that parameter $P$ has adjustment infeasibility factor $IF$</td>
<td>belief(agent, \text{has_infeasibility_factor}(P: PARAMETER, IF:REAL))</td>
</tr>
<tr>
<td>The agent believes that the action option to adjust parameter $P$ from $W_1$ to $W_2$ has infeasibility rank $R$</td>
<td>belief(agent, \text{has_action_option_rank}(adjust_to(P: PARAMETER, W_1:REAL, W_2:REAL), R:REAL))</td>
</tr>
<tr>
<td>The agent believes that the feasibility threshold is $FT$</td>
<td>belief(agent, \text{feasibility_threshold}(FT:REAL))</td>
</tr>
<tr>
<td>The agent proposes the action to adjust parameter $P$ from $W_1$ to $W_2$</td>
<td>action_proposal(agent, adjust_to(P: PARAMETER, W_1:REAL, W_2:REAL))</td>
</tr>
</tbody>
</table>

**SDR4 Heuristic generation of channel action options for low emotion members**

If the ambient agent believes that $A$ is a low emotion member
and that a group emotion deficient $ED$ at $T$ was identified
and that the adjustment extent is $AE$
and the channel from $A$ to $B$ has strength $C$
then the agent will believe that an action option is to change the value $C$ for channel strength
to $C - AE*ED*C$
belief(agent, \text{low\_emotion\_member}(A)) &
assessment(agent, group_emotion_deficient_at(ED, T)) & belief(agent, adjustment_extent(AE)) & belief(agent, has_channel_strength(A, B, C)) → belief(agent, action_option(adjust_to(channel_strength(A, B), C, C - AE*ED*C)))

**SDR5 Heuristic generation of openness action options for low emotion members**
If the ambient agent believes that $A$ is a low emotion member and a group emotion deficient $ED$ at $T$ was identified and it believes that the adjustment extent is $AE$ and the openness of $A$ is $D$ then the agent will believe that an action option is to change the value $D$ for openness to $D + AE*ED*(1-D)$

belief(agent, low_emotion_member(A)) & assessment(agent, group_emotion_deficient_at(ED, T)) & belief(agent, adjustment_extent(AE)) & belief(agent, has_openness(A, D)) → belief(agent, action_option(adjust_to(openness(A), D, D + AE*ED*(1-D))))

**SDR6 Heuristic generation of expressiveness action options for high emotion members**
If the ambient agent believes that $A$ is a high emotion member and a group emotion deficient $ED$ at $T$ was identified and it believes that the adjustment extent is $AE$ and that the expressiveness of $A$ is $E$ then the agent will believe that an action option is to change the value $E$ for expressiveness to $E + AE*ED*(1-E)$

belief(agent, high_emotion_member(A)) & assessment(agent, group_emotion_deficient_at(ED, T)) & belief(agent, adjustment_extent(AE)) & belief(agent, has_expressiveness(A, E)) → belief(agent, action_option(adjust_to(expressiveness(A), E, E + AE*ED*(1-E))))

**SDR7 Heuristic generation of channel action options for high emotion members**
If the ambient agent believes that $A$ is a high emotion member and that a group emotion deficient $ED$ at $T$ was identified and that the adjustment extent is $AE$ and that the channel from $A$ to $B$ has strength $C$ then the agent will believe that an action option is to change the value $C$ for channel strength to $C + AE*D*(1-C)$

belief(agent, high_emotion_member(A)) & assessment(agent, group_emotion_deficient_at(ED, T)) & belief(agent, adjustment_extent(AE)) & belief(agent, has_channel_strength(A, B, C)) → belief(agent, action_option(adjust_to(channel_strength(A, B), C, C + AE*ED*(1-C))))
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SDR8 Heuristic generation of openness action options for high emotion members
If the ambient agent believes that \( A \) is a high emotion member and a group emotion deficient \( ED \) at \( T \) was identified and it believes that the adjustment extent is \( AE \) and that the openness of \( A \) is \( D \) then the agent will believe that an action option is to change the value \( D \) for openness to \( D - AE*ED*D \)
\[
\text{belief}(\text{agent, high\_emotion\_member}(A)) \land \text{assessment}(\text{agent, group\_emotion\_deficient\_at}(ED, T)) \land \text{belief}(\text{agent, adjustment\_extent}(AE)) \land \text{belief}(\text{agent, has\_openness}(A, D)) \\
\rightarrow \text{belief}(\text{agent, action\_option(adjust\_to(openness(A), D, D - AE*ED*D)))}
\]

SDR9 Ranking action options
If the ambient agent believes that an action option is to change the value \( W_1 \) for \( P \) to \( W_2 \) and it believes that \( P \) has infeasibility factor \( IF \) then the agent will believe that the action option has infeasibility rank \( IF^*(W_2-W_1) \)
\[
\text{belief}(\text{agent, action\_option(adjust\_to(P, W_1, W_2)))} \land \text{belief}(\text{agent, has\_infeasibility\_factor}(P, IF)) \\
\rightarrow \text{belief}(\text{agent, has\_action\_option\_rank(adjust\_to(P, W_1, W_2), IF^*(W_2-W_1)))}
\]

SDR10 Generation of action proposals
If the ambient agent believes that the action option has infeasibility rank \( R \) and that the feasibility threshold is \( FT \) and \( R \leq FT \) and \( R \geq -FT \) then it will generate the action option as an action proposal.
\[
\text{belief}(\text{agent, has\_action\_option\_rank(adjust\_to(P, W_1, W_2), R)}) \land \text{belief}(\text{agent, feasibility\_threshold}(FT)) \land \text{R}\leq FT \land \text{R}\geq -FT \\
\rightarrow \text{action\_proposal(agents, adjust\_to(P, W_1, W_2))}
\]

2.9 Simulation Results of the Ambient Agent Model
To illustrate the group emotion support model described in previous sections, by a specific example, a specific scenario is addressed. The simulation for the analysis process for an absorption case is discussed in Section 2.9.1. Section 2.9.2 shows the simulation for the support mechanisms. Similarly simulation results for an amplification case are presented in Sections 2.9.3 and 2.9.4.

2.9.1 Simulation of analysis process of absorbed emotion contagion
In this section the simulation results of the analysis process are shown in an example scenario for absorption that represents a situation where the group emotion is happiness and is analyzed by the ambient agent. The LEADSTO software environment [8] has been used to perform a number of simulation
experiments. In this example, the ambient agent generates beliefs on the individual emotion levels of three group members, named Arnie, Bernie and Charlie (see ADR2), and of the group emotion level at different points in time (see ADR5). The agent also assesses the (expected) group’s emotion deficient at a future time point based on its belief of the group emotion level and the norm for the group emotion level. The norm of the group emotion can be set by the modeler and represents in this example an optimal level of happiness, at which the team can perform as optimal as possible. The norm was set to 0.62 in this example.

Table 2.4 Parameter Settings Example

<table>
<thead>
<tr>
<th></th>
<th>Arnie</th>
<th>Bernie</th>
<th>Charlie</th>
</tr>
</thead>
<tbody>
<tr>
<td>Initial emotion level $q$</td>
<td>0.9</td>
<td>0.05</td>
<td>0.3</td>
</tr>
<tr>
<td>expressiveness $\varepsilon$</td>
<td>0.6</td>
<td>0.5</td>
<td>1</td>
</tr>
<tr>
<td>outgoing channel strengths $\alpha$</td>
<td>0</td>
<td>0.6</td>
<td>0.6</td>
</tr>
<tr>
<td>openness $\delta$</td>
<td>0</td>
<td>0</td>
<td>0.9</td>
</tr>
<tr>
<td>relevance $\rho$</td>
<td>0.34</td>
<td>0.33</td>
<td>0.33</td>
</tr>
</tbody>
</table>

In this example scenario, Arnie is very happy (initial emotion level = 0.9), he can not receive other emotions (because his $\delta$ and receiving $\alpha$’s are zero), however, he is able to send emotions (his $\varepsilon$ is not zero). Bernie is not happy (initial emotion level is 0.05), he can not receive emotions (his $\delta$ is zero), but he can send emotions (his $\varepsilon$ is not zero). The contagion strengths toward Arnie and Bernie are zero. If these strengths stay zero, Arnie and Bernie will stay on the same emotion level. Finally, Charlie is also not happy (initial emotion level = 0.3), but he can receive and send emotions quite strongly (because his $\delta$ is 0.9 and his $\varepsilon$ is 1). For an overview of the settings, see Table 2.4.

In Figure 2.11 a simulation trace is shown in which the horizontal axis represents time, and the vertical axis represents quantitative information about generation of ambient agent’s beliefs on the individual and group emotion levels at different (future) time points. In this situation the total group emotion level goes from 0.64 to 0.59 in 500 time steps. This means that the group emotion level is above the norm of 0.62 at first, but will get below this norm later. The idea of the analysis model is that our ambient agent predicts this downward development early in time (long before it actually happens), so it can propose appropriate actions to the team leader early in time, to prevent this from happening. The simulations are based on step size $\Delta t = 0.1$.

In Figure 2.11, on the x-axis time is represented and goes from 0 to 0.7. This is the processing time of the ambient agent. The idea is that the agent reads the
emotions of the persons at time point 0 and from that time point ambient agent starts to generate beliefs on the development of the emotion levels of the group members and the group as a whole. This simulation can be found in all the graphs of the individual and group emotion. The developments of the emotion levels (simulated by the ambient agent from time point 0 to 0.5) are estimated for the future time points 0 to 5. Figure 2.12 shows the assessment of the expected emotion deficient by the ambient agent (see ADR6). Only the part is shown where an assessment is generated. At time point 0.55 on the x-axis the ambient agent makes an assessment of the future group emotion level deficient for time point 5. The ambient agent assesses that on future time point 5 indeed there is a group emotion deficient to be expected (of about 0.027).

Figure 2.11 Simulation trace of the analysis process for emotion absorption
2.9.2 Simulation of the support process of absorbed emotion contagion

In this section the example scenario of the previous section is extended with the support of the ambient agent. The assumption is made that Arnie is working separately from Bernie and Charlie; i.e., he works in a different office than Bernie and Charlie. Therefore, Arnie’s channels to Bernie and Charlie have strength 0. Previously, the ambient agent assessed that there is a nonzero emotion deficient expected: the group emotion level slowly gets below the group emotion level norm of 0.62. Therefore, based on its heuristics, the ambient agent detects which group members are high or low emotion members, and generates action options that decrease or increase parameters related to these members: expressiveness, openness or channel strength. After ranking these options, the agent proposes to the group leader those options, which do not exceed a certain feasibility threshold. An example of (a part of) such a trace is shown in Figure 2.4. Here, time is on the horizontal axis, and state properties are on the vertical axis. A dark box indicates that a state property is true. Figure 2.4 shows that the ambient agent detects the high and/or low emotion members (Arnie is detected as a high emotion member and Bernie as a low emotion member.) (see SDR1 and SDR2), the action-options are ranked (see SDR9) and the ambient agent proposes the actions that do not exceed the feasibility threshold to the group leader (see SDR10).

2.9.3 Simulation of the assessment of amplified emotion contagion

In this section the simulation results of the analysis process are shown in an example scenario for an amplification case. The ambient agent generates beliefs on the individual emotion levels of three group members, named Arnie, Bernie and Charlie (see ADR2), and of the group emotion level at different points in time (see ADR5). The agent also assesses the (expected) group’s emotion deficient at a future time point based on its belief of the group emotion level and the norm for the group emotion level. The norm of the group emotion can be set by the modeler and represents in this example an optimal level of happiness, at which the team can perform as optimal as possible. The norm was set to 0.60 in this example.

In this example scenario Arnie, Bernie and Charlie are all not very happy (initial emotion levels are 0.3 and 0.1). They are all very open to receive each other’s happiness; all have an openness $\delta$ of 0.9.
Arnie can send his emotions most effectively to others, because his contagion strength, which is his channel $a$ multiplied by his expressiveness $e$, is 0.72 for both Bernie and Charlie. Bernie can send emotions less effectively, his contagion strength is 0.45. Charlie can send his emotions with even less power: his contagion strength is 0.09. For an overview of the settings, see Table 2.5.

**Table 2.5. Overview of the parameter settings**

<table>
<thead>
<tr>
<th></th>
<th>Arnie</th>
<th>Bernie</th>
<th>Charlie</th>
</tr>
</thead>
<tbody>
<tr>
<td>Initial emotion level $q$</td>
<td>0.3</td>
<td>0.1</td>
<td>0.1</td>
</tr>
<tr>
<td>Impact $\beta$</td>
<td>0.3</td>
<td>1</td>
<td>0.6</td>
</tr>
<tr>
<td>Contagion strength $e_a \cdot \alpha_{ab}$</td>
<td>0.72</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Contagion strength $e_b \cdot \alpha_{ba}$</td>
<td>0.72</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Contagion strength $e_c \cdot \alpha_{cb}$</td>
<td>0.09</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Contagion strength $e_c \cdot \alpha_{ca}$</td>
<td>0.09</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Openness $\delta$</td>
<td>0.9</td>
<td>0.9</td>
<td>0.9</td>
</tr>
<tr>
<td>Relevance $\rho$</td>
<td>0.34</td>
<td>0.33</td>
<td>0.33</td>
</tr>
</tbody>
</table>

In Figure 2.13 a simulation trace is shown in which the horizontal axis represents time, and the vertical axis represents quantitative information about generation of ambient agent’s beliefs on the individual and group emotion levels at different (future) time points. In this situation, the total group emotion level goes from 0.49 downwards and through an upwards spiral mechanism to 0.58 in 500 time steps. This means that the group emotion level is always below the norm of 0.60. In this analysis model, our ambient agent predicts the future development of the group emotion level and this prediction shows that it will stay below the norm for all the future time steps. In this case it can propose appropriate actions to the team leader early in time, to help the group emotion level get above the norm faster. The simulations are based on step size $\Delta t = 0.1$.

On the x-axis in Figure 2.13, time goes from 0 to 1. This time actually represents processing time of the ambient agent. The idea is that the agent reads the emotions of the persons at time point 0 and from that time point the ambient agent starts to generate beliefs on the development of the emotion levels of the group members and the group as a whole. The developments of the emotion levels (simulated by the ambient agent from time point 0 to 0.5) are estimated for real future time points 0 to 5. At time point 0.5 on the x-axis,
the agent makes the assessment of an expected emotion deficiency for real future time point 5. The ambient agent assesses that on future time point 5, there is a group emotion deficiency to be expected (of about 0.04).

\[
\text{assessment(agent, group_emotion_deficient(Norm-GroupEmotionLevel))}
\]

\[
\text{belief(agent, group_emotion_level(X))}
\]

Figure 2.12 Simulation trace of the analysis process for emotion amplification

2.9.4 Simulation of the support process for amplified emotion contagion

In this section, the example amplification scenario of the previous section is extended with the support of the ambient agent. The assumption is made that Arnie, Bernie and Charlie are working on a task together that is perhaps stressful, since they are not very happy (initial emotion levels are 0.3 or 0.1). Arnie is very charismatic and he works together a lot with Bernie and Charlie, this is represented in his high contagion strength. Charlie on the other hand is very introvert and therefore his contagion strength is weak. Bernie has a medium contagion strength. All three are open to receive happy emotions from others, since they all have a high level of openness. In the previous section it was shown that the ambient agent predicted the future development of the group emotion level, namely an upward spiral that still was below the norm at future time point 5. Therefore, based on its heuristics, the ambient agent detects which group members are high or low emotion members, and generates action options that decrease or increase parameters related to these members: expressiveness or channel strength. After ranking these options, the agent proposes to the group leader those options, which do not exceed a certain feasibility threshold. An example of (a part of) such a trace is shown in Figure 2.14. Here, time is on the horizontal axis, and state properties are on the
vertical axis. A dark box indicates that a state property is true. Figure 2.14 shows that the ambient agent detects the high and/or low emotion members (Charlie is detected as a high emotion member and Bernie as a low emotion member.) (see SDR1 and SDR2), the action-options are ranked (see SDR9) and the ambient agent proposes the actions that do not exceed the feasibility threshold to the group leader (see SDR10).

![Simulation trace of a support process for amplified emotion contagion](image)

**Figure 2.13** Simulation trace of a support process for amplified emotion contagion

### 2.10 Discussion

Within teams performing critical tasks, a team leader is responsible for a good spirit in the team. Due to high pressure, emotions within the team may easily take the form of a negative spiral. Therefore, it is challenging to regulate such patterns. Recent literature on emotion contagion spirals addresses how such spirals may occur. Most existing computational models of emotional processes represent emotion as a process or state that depends on observed stimuli by a single agent; e.g., [8], [22], [28]. These models of emotion differ from our proposed model, in that the focus in these models lies more on individual emotions, not on collective emotion. Recently researchers have started to investigate emotions in a social context more extensively. For the work reported in the current chapter, more specific work on emotion contagion spirals was taken as a point of departure; cf. [9], [10], [11]. In the current chapter, first a multi-agent-based model for emotion contagion spirals has been presented and analyzed. Although an extensive empirical validation is left for future work, it turned out that the model is able to produce various interesting emerging patterns as described...
(informally) in the psychological literature, including the upward and downward emotion spirals discussed in [10]. Although this is not an exhaustive proof, it is an important indication that the model behaves as expected. In contrast to most existing (symbolic) agent-based modelling approaches, the current approach represents a multi-agent system using numerical techniques.

Literature on computational models of emotion contagion is scarce. The only computational models that come close to the process modelling of this current work can be found in the area of social science, named social diffusion modelling. Examples of social diffusion models are: the diffusion of social movements like political interests and parties, see [17], and crowd behaviour, as in emergency evacuation, see [23]. Most social diffusion models follow the diffusion of innovations model of Rogers, in which it is posed that the diffusion process of innovations proceeds in the form of an S-shaped curve: the contagion of an innovation starts slow, but then accelerates rapidly, followed by a rapid deceleration [26]. Even though social diffusion models can simulate the contagion of a certain innovation and use similar concepts as the current work does, such as a sender, receiver and communication channel, these computational models of social diffusion also differ from our model, in the way that they model the complex spread of innovations as diffusion that is asymmetric in time, irreversible, and nondeterministic. Our model of emotion contagion, models the continuous spread of emotions among the group members over time, which can have many patterns in it and is reversible in time.

The model for emotion contagion was taken as a point of departure for an ambient agent model that uses the computational model to assess the expected emotion levels at future time points, and to propose actions to the team leader to regulate these levels. The generic agent model for human-aware ambient intelligence applications described in [5] was taken as a point of departure. One of the possible applications of the resulting ambient agent model could be analyzing and supporting group emotion in virtual meetings. For example, when two groups at two locations in the world are video-conferencing, a software agent could measure the group emotion of both groups and could show the emotion level of the other group to the group leaders. The ambient software agent could then, if necessary, provide support to the group leaders, e.g. when is the best time to let the other

---

2 The question to what extent our model is able to simulate such completely different processes is beyond the scope of this paper. Although these processes share some characteristics with the process of emotion contagion, for other factors (e.g. openness, or the tendency to adapt emotions upward or downward) it is not trivial to find a counterpart.
group make a decision, or how to calm the other group down after their anger level got too high during decision making.

In follow-up research, more attention will be paid to the model’s more detailed external validation of the model for emotion contagion spirals. The mathematical and automated analyses described above have been successfully performed to guarantee internal validity, and it fits to patterns described informally in (social) psychological literature. Nevertheless, this does not guarantee that the model is directly applicable to humans in a more detailed and more quantitative manner, and in particular it does not show which personality parameter values fit which person. Therefore, as a next step, a more detailed validation of the model in laboratory experiments is planned. The idea is to create a setting in which various humans interact in a room, while continuously being subject to (physiological) measurements (e.g., using emotion recognition approaches as discussed in [14]) to assess their emotions. The obtained data can then be used in order to fine-tune the model using adaptive and machine learning techniques. This will not only provide a more detailed validation of the model, but also result in realistic parameter settings for different types of individuals.

Concerning further work, a number of factors can be refined or added to the model. For instance, recently a new perspective has emerged that describes leaders as the managers of group emotions [24]. According to this perspective, every group member can assume a leadership role by providing certainty and direction during times of ambiguity to create shared emotion within the group. The gender of this group leader also has an important impact on the emerging emotion contagion processes.

A final possibility to extend the model is to consider multiple emotions. Currently, the group contagion spirals of only one emotion can be modelled. It will be interesting, for example, to study the impact of simultaneous occurrences of happiness and anger within the same group, or the interaction between anger and fear within a group. For specific types of emotions, specific values may have to be estimated, e.g. $\alpha, \delta, \rho$. However, if also interaction between different emotions is to be addressed (for example, anger in one person affecting fear in another person), more specific work is needed, which is planned for the future.

References


Chapter 3 - Do Positive Emotions Broaden the Thought Action Repertoire, Creativity and Memory? A Replication and Extension Study

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Abstract: The broaden-and-build theory (Frederickson (1998, 2001) hypothesises that positive emotions broaden the scope of thought action repertoires and negative emotions narrow this scope. Three experiments with respectively 101, 60 and 60 university students and employees tested these hypotheses. In each experiment participants viewed a short movie clip that elicited (1) happiness, (2) hope, (3) neutrality, (4) anxiety or (5) sadness. Thought-action repertoires were assessed using a Verbal Twenty Statement Test (Experiment 1), creativity was assessed with a three creativity tests measuring divergent and convergent thinking and memory was assessed with three memory task that measured gist, central and background memory. In Experiment 1 and 2, no effect of positive or negative emotions, in comparison to a neutral state were found on the number of action urges and the levels of creativity people have. Also, no effects of positive and negative emotions on the types of actions and thoughts people have were found in a content analysis of the action urges in Experiment 1. Only in Experiment 3, modest support for the broaden-and-build theory was found. Compared to a neutral film, watching a negative film decreases gist and central aspects of memory and watching a positive film, increased central and background aspects of memory.
3.1 Introduction

Emotions are often defined as elicited by a particular stimulus, they often include psychological reactions, and are relatively intense and short-lived (Frijda 1986). Emotions can influence various cognitive abilities, like decision making, action preparation and memory. In Antonio Damasio’s *Somatic Marker Hypothesis* it is explained how decision options are somatically marked within the brain, so that each choice induces (via an emotional response) a feeling in the body that helps you make a decision. (Damasio, 1996). A positive marker linked to a particular option occurs as a positive feeling for that option and a strong negative marker as a strong negative feeling for that option.

Psychologists have explained the emotional influence on actions and thoughts as *action tendencies* (Frijda, 1986, Lazarus, 1991). For example, Frijda explains emotions as states of action readiness, which can gear us to flee a dangerous situation.

Barbara Frederickson argues that unlike negative emotions, positive emotions do not lead to specific action tendencies (Frederickson 1998, Frederickson & Branigan, 2001; Frederickson & Levenson 1998). Frederickson’s *broaden-and-build theory* poses that negative and positive emotions have a distinct and complementary function. Her broaden hypotheses poses that positive emotions broaden individual’s momentary thought-action repertoires, prompting them to pursue a wider range of thoughts and actions than is typical (e.g. play, explore, savour, and integrate). (Frederickson 1998, 2001). The complementary narrowing hypothesis states that negative emotions narrow individual’s momentary thought-action repertoires by calling forth specific action tendencies (e.g. attack, flee).

The motivation for the current research is two-folds. First, the reason for this research was to reproduce previous research results of Experiment 2 in Frederickson & Branigan (2005) based on the broaden-and-build theory and to extend these results with testing the theory in two new cognitive abilities: creativity and memory. The second reason was that an experiment was needed to collect natural human speech without the subjects knowing that it was meant for emotion recognition research. (Kowalczyk & Wal, 2011). In the current experimental setting, subjects would be induced with very positive or negative emotions and the collected speech would be very useful for recognizing emotions by a machine algorithm. For this reason, all tests were taken verbally, instead of written.

In Frederickson & Branigan (2005), it was found that, compared to a neutral emotion, the positive emotions amusement, contentment and serenity increased participant’s thought-action repertoires and the negative emotions anger, disgust, fear and anxiety decreased participant’s thought-action repertoires. The goal of Experiment 1 of the current research is to reproduce
similar results, by using the same thought-action repertoire test, but with different film clips, that induce the positive emotions: happiness and hope, negative emotions: anxiety and sadness and a neutral emotion. Different film clips were used, because not all of the same emotions as the original research were chosen and because information about the original film clips was requested per email but no answer was given. It is expected that, compared to a neutral emotion, happiness and hope broaden participant’s thought action repertoires and that anxiety and sadness narrow participant’s thought-action repertoire.

In Experiment 2 of the current research, it is investigated if anxiety and hope (a negative and positive emotion) have effect on people’s creativity, compared to a neutral emotion. Research into the effects of affect on creativity show different results. Fredrickson (1998, 2001, Frederickson & Branigan, 2005) argues that positive emotions may broaden a person’s psychological resources, such as creativity. Thus, being in a positive mood may help the person to be more creative, as it broadens their thought-action repertoires and therefore, the person has more resources that can be accessed. However, it is also argued that high levels of creativity are correlated to negative mood. Evidence for the hypothesis that negative affect may be associated with higher levels of creativity can be taken from a study by Verhaegen, Joorman and Khan (2005). They suggested that past depressive symptoms predict higher divergent thinking scores and more creative interests. However, it has to be noted that they have based this conclusion on the hypothesis that self-reflective rumination is the key predictor of this increase in creativity. A ‘healthy’ individual who is in a bad mood may, in this case, not be compared to an individual suffering from depression or an anxiety disorder, as this person is not likely to ruminate for a long period of time. Yet, the study by Verhaegen, Joorman and Khan (2005) is invaluable as it does give a perspective on the link between depression and creativity. More indications of the correlation between high levels of creativity and negative affect, namely that of depression and anxiety disorders, can be found in: (Andreasen, 1987; Verhaeghen, Joorman, & Khan, 2005; Rubinstein, 2008). Someone suffering from social-phobia, for instance, will come up with all sorts of creative solutions to avoid their fear and therefore, it could be argued that these individuals are more creative. Nevertheless, anxiety may also be associated with shyness, as shyness is a subclinical region of social anxiety (McNeil, 2001). Studies on shyness have demonstrated that shyness predicted less creativity in poem-writing tasks (Cheek & Stahl, 1986) and thus, by extension, social anxiety or social phobia, may be associated with less creativity (Silva & Kimbrel, 2010). Overall, it seems that affect, whether it is positive or negative, has an effect on creativity, whether it is a decreasing or increasing effect. Therefore it is expected that in
Experiment 2, compared to a neutral emotion, hope and/or anxiety will have an effect on creativity: either increasing or decreasing creativity. Creativity will be tested with a combination of three creativity tests, inspired by Beghetto and Kaufman (2007), Guilford (1967) and Wallas and Kogan (1965).

In the third experiment of the current research, the effect of happiness and sadness (a positive and negative emotion), compared to a neutral emotion, on different aspects of memory are investigated. Several studies have demonstrated that emotions have influence on the central and background (peripheral) details of memory. Easterbrook (1959), formulated the hypothesis that emotional arousal (especially negative emotions like sadness and fear) cause a narrowing of attention, that in its turn, causes a focus on the central information and not the background (peripheral) details of the stimulus or event. Other studies found similar effects. In (Burke et al. 1992), emotion improved memory for gist and basic-level visual information, but in contrast, undermined memory for details. Loftus and Burns (1982) found that impaired memory occurred only when the event that had to be recalled by the participants was mentally upsetting, and not when it was merely unexpected but not upsetting. Clifford en Hollin (1981) found that the participants’ memories were less accurate when they had seen a violent incident, than when they had seen a emotionally neutral incident. Other findings that support this hypothesis, are findings of the weapon focus effect, which is often observed in witnesses and victims of crimes. (Loftus et al. 1987). The witness of a crime often concentrate their attention on the weapon of the perpetrator, which results in a detailed memory of the weapon, but a poor memory of details, like the clothes and facial characteristics of the perpetrator. Besides the central-background information trade-off in memory, there is also the ‘gist’ memory versus visual detail memory trade-off in memory. (Adolphs et al. 2001).

Kensinger et al. 2007b, investigated the effect of negative emotions on the two trade-offs in memory. They found that individuals can show a central/peripheral trade-off for both the visual detail and the gist of a scene. Also, when a gist/detail trade-off is elicited, it interacts with the central/peripheral trade-off.

Other studies have investigated the effect of positive emotions on memory as well. Kensinger and colleagues (Kensinger et al. 2007a) investigated if there is a difference in the amount of visual detail remembered when retrieving positive, neutral or negative objects. Their results demonstrated that negative (not positive) content enhanced the visual specificity of memory of young and older adult, but positive content conferred a general memory advantage only for older adults. Anderson and Shimamura (2005) investigated film content memory, word recall and context recognition under four different conditions: listening to words while viewing a neutral, positively valenced,
negatively valenced, or arousing film clip. Context memory performance was disrupted when words were presented during negatively valenced film clips, whereas it was enhanced when words were presented during arousing film clips. Free recall of words presented during the negatively valenced films was also disrupted. Their findings suggest that both positive and negative emotions can influence memory performance.

More studies investigating the effect of emotions on memory are necessary, especially ones that investigate if there is a different effect of positive versus negative emotions on memory, compared to a neutral emotion. The current research investigates if, compared to a neutral emotion, happiness and sadness have a decreasing or increasing effect on the ‘gist’ memory and the central and background memory of events. The ‘gist’, central and background aspects of memory will be measured by a memory task inspired by Beghetto & Kaufman (2007), Wallas and Kogan (1965) and Mednick (1962). It is expected that, according to the broaden-and-build theory, the positive emotion ‘happiness’ will broaden the attention and therefore causes an improvement in the gist, central and background memory. The negative emotion ‘sadness’ is expected to cause a narrowing of attention according to the broaden-and-build theory, weapon focus effect and cue utilisation theory (Easterbrook, 1959) and therefore decreasing the background memory performance, but increasing the gist and central memory aspects. Both effects are expected in comparison to the memory performance in the neutral condition.

**EXPERIMENT 1, 2 AND 3**

### 3.2 Method

**Participants**

The total number of participants was 111 Dutch university students and Dutch employees (49.5% women, average age: 28.47 years, age range [18, 65], employees were associate professors and supporting staff). The participants of Experiment 1, 2, 3 are all a subset of the total number of participants. Experiment 1: participants were 101 university students and employees (47.5% women). Experiment 2: participants were 61 university students and employees (57.5% women). Experiment 3: participants were 60 university students and employees (46.7% women). For all experiments, participants were randomly recruited from the campus terrain through flyers promoting the research and each participant received 5 euro.
Materials

Written. Emotional experiences were assessed using an Emotion Report Form, based on the Geneva Appraisal Questionnaire (GAQ, 2002) and the emotion report form used by Frederickson and colleagues. (Fredrickson et al. 2000). Participants rated how much they felt each of the following 16 emotions: sadness, fear, shame, contentment, guilt, happiness, disgust, despair, positivity, enjoyment, irritation, hope, anger, pride, negativity, anxiety. Ratings were made on a 10-point Likert scale (1 = none, 10= a great deal).

<table>
<thead>
<tr>
<th>Experiment</th>
<th>“Hope”</th>
<th>“Happy”</th>
<th>“Neutral1”</th>
<th>“Neutral2”</th>
<th>“Anxiety”</th>
<th>“Sadness”</th>
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<tr>
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<td>20</td>
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<td>Experiment 3</td>
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</table>

Visual. 6 videotaped film clips served as the experimental manipulation in this research. All film clips lasted 5 minutes. Two clips elicited two distinct negative emotions: “Anxiety’ showed anxious scenes from ‘saw’ movies, the movie ‘the Shining’ and ‘Deep Blue ‘Sea’, so that the participant would jump or left him anxious and confused. “Sadness” showed two scenes, one of the movie Sophie’s Choice, where the main character has to choose which of her two children will die and one of Schindler’s List, where a German officer shoots Jewish prisoners. “Sadness” was meant to induce a lot of negativity and sadness. Two additional clips were intended to elicit two distinct positive emotions happy and hope, but seemed both to induce the same positive emotions with the same intensity. Here, they are described with their originally intended labels, to make the distinction between the content clear. “Happy” showed a comical scene of Mr. Bean, a comical Dutch cabaret show, funny scenes with animals and a scene where Golden Retriever puppies are running and playing on the grass. “Happy” was meant to induce a lot of positivity and happiness. “Hope” shows excerpts from Disney films, a gospel choir and a rose blooming, so that participants were reminded of their childhood and to make them more hopeful. Two final clips served as a neutral control condition. “Neutral 1” showed short clips of a car driving on the road, a working mill, a person explaining a mathematical problem and an extract of a youtube self-help course video on how to use a computer, “Neutral 2” contained a short clip from a program on concrete pipes, a short clip from a program on lego and two television advertisements of teleshopping products. Both ‘neutral’ film clips
were meant to keep the participants into a neutral state of mind, not particularly anxious, sad, hopeful or happy. Both ‘neutral’ film clips were meant to be equally neutral.

**Dependent measures**

*Experiment 1.* Breadth of momentary thoughts was assessed using a modified, open-ended Twenty Statements Test (Kuhn & McPartland, 1954), like in (Frederickson & Branigan, 2005). Just after viewing the film, the experimentator would give the following instructions to the participant in Dutch (free translation into English):

> Take some distance from the specific events in the film, but concentrate on the emotion the movie induced in you. Take a moment and imagine yourself being in a situation in which you experience the same emotion. Try to keep a concentrated focus on this emotion. Focus really good on this emotion and experience the situation very specific and complete. You may close your eyes to concentrate better. When you are experiencing the situation vividly and deeply, give me a sign…

When the participant gave a sign, the experimentator followed with:

> Name, within a maximum of 2 minutes time, as many things you would like to do right now. These things can be anything, use your imagination…

The participants gave their answers verbally and the number of things they named were tallied. Higher scores indicated a larger thought-action repertoire.

An exploratory content analysis of participant’s responses was also conducted. All audio recordings were played and answers were written down verbatim. (2 audio recordings are missing, due to defect recorder). One of the researchers and one independent coder classified each response. All categories named in (Frederickson & Branigan, 2005) were used, except the category relish/reminisce, because it could not be applied to the data. Three extra categories were chosen to be able to put all answers in categories that are mutually exclusive. The categories are: eat/drink, read, relax/sleep (e.g. listening to music, take a bath, go to bed), schoolwork/work (e.g. go to lecture, do my homework, finish my to-do list), exercise/sport (e.g. doing sports, bungee jumping, swimming), outdoors/nature (e.g. lie in the grass, feel the sun on my skin, go to the beach), play (play with my dog, play with my children), be social (going to my friends, talking to my mom, go to a party), be antisocial (fight, flee, yell), very positive feelings and thoughts (e.g. fly, going to the moon, laugh), travelling/holiday (e.g. going on holidays, travelling, going to Barcelona), development/future plans (e.g. buying a house, learning a new
language, learning to drive a car) and doing something fun (e.g. doing something fun). Interrater agreement was 85%. For each participant, proportion scores were determined for each activity by dividing the tally for that activity by the total number of statements the participant generated.

**Experiment 2.** Three different methods were used to measure creativity, because theories on the best way to measure creativity have been inconclusive, as there is no one sense in which someone is creative (Beghetto & Kaufman, 2007). The first method utilised was based on Guilford’s (1967) alternative uses task. This method assesses the divergent thinking ability of an individual. Within the current experiment, participants were asked to name all the things one could do with: a newspaper, a DVD, a paperclip and a brick. For each of these items a maximum time span of two minutes was given before moving on to the next item. Furthermore, participants were told that they could let the experimenter know when they could not come up with any more uses for this item even if the two minutes had not passed yet. The second method used in this creativity test, was based on Wallas and Kogan’s (1965) assessment of creativity, which is another method to examine the divergent thinking ability of a person. Within the current experiment, participants were asked to name as many things that have: a tail, a diamond (shape), wheels, and a knob. Similarly as to the Guilford based test, a maximum time span of two minutes was given before moving on to the next item. Again, participants were told that they could let the experimenter know when they could not come up with any more uses for this item even if the two minutes had not passed yet. The third and last method utilised in this experiment, was based on Mednick’s (1962) remotes associations task, which concentrates on a person’s convergent thinking ability. The task was originally written in English, so a shortened and modified version was made in Dutch, as items on this task could not directly be translated. Within this task, participants are present with three words and are asked to come up with the word that associates the other three together. A total of eight items were shown on a television screen, in turn, to the participant. Moreover, as soon as the item was visual on the screen, the experimenter read the item out loud. Before the eight items were shown, a trial item was shown to explain what was being asked from the participant. It was explained that participants would have thirty seconds to give the experimenter the right answer before the experimenter would move on to the next item. Once the participant had told the experimenter to completely understand the task, the real experiment was started.

**Experiment 3.** Memory was measured with a memory task called the “Recognition Task”, originally developed by Heuer and Reisberg (1990), later adjusted by Burke and colleagues (1992) and used by Libkuman and colleagues (1999). For the movie clips “Happy”, “Sad” and “Neutral2” similar memory
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tasks were created. Every memory task consisted of 15 multiple choice questions: five questions about the *gist* of the story, five questions about the *central* details and five questions about the *background* details. The *gist* of the story is about information, essential for the story line, an example question for the “Sadness” movie clip is: “What does the German officer ask the woman to do?”. *Central* details is about non-essential information that is associated with the central characters and objects in the scene, for example what does the main character in the movie wear? An example question for the “Sadness” movie clip is: “What does the shooter wear?”. The *background* details are about non-essential information that is not associated with the central characters and objects in the scene. An example question for the “Happy” movie clip is: “What can be seen in the background in the scene with the puppies?”. All fifteen questions were presented to the participants on a tv-screen with Microsoft Office Power Point. Every slide contained one question with four multiple choice answers. If the participant did not know the answer, he was asked to guess. The number of correct answers per category (*gist*, *central* or *background*) are summed, whereby a maximum score of 5 could be achieved on each category.

**Procedure**

Participants were tested individually. On arrival, they were seated in a comfortable orange sofa in a well-lit living room-like research lab, and provided their informed consent. After welcoming the participant, the experimenter located herself in another room, making the participant feel at ease and able to experience his/her emotions alone. The participants were seated 2 meters in front of a 40 inch flat-screen tv, which displayed film clips and memory task items. A laptop with Skype was located in front of them on a living-room table, next to the written material: the Emotion Report Forms. The Instructions to all tests and the single Verbal Thought-action Repertoire Test Item were given verbally to the participant. The Creativity Test and Memory Test Items were displayed on the tv-screen. Participants gave their answers verbally, through Skype.

Each participant of the total number of participants performed two tasks out of the possible three: the thought-actions repertoire test (Experiment 1), the creativity test (Experiment 2) and the memory test (Experiment 3) and watched two film clips out of the possible 6: “Happy”, “Hope”, “Anxiety”, “Sadness”, Neutral1” and “Neutral 2”. For all the participants, the order of the two film clips and of the two tasks were randomised, to control for order effects. Participants were randomly assigned to the experimental or control conditions.
After entering the research lab and giving informed consent, each participant started with filling in a first Emotion Report Form. Thereafter, each participant would watch a film clip and perform one of the three possible tasks straight after the movie, followed by filling in the Emotion Report Form. After a 2 minute break that could clear the participant’s head and feelings, the participant would watch the second movie clip, perform a second task and fill in the Emotion Report Form.

3.3 Results

Overview and analytic strategy
First, it was confirmed that the film clips altered the subjective emotional experiences as intended. Then, one-tailed a priori contrast were used to test the broaden and narrowing hypothesis, which are theory-driven and directional.

Manipulation check
To confirm that the 6 film clips influenced the subjective experiences of the participants, as intended, the responses on the Emotion Report Forms were examined. The modal and mean emotion ratings for each film and each of the 16 emotions are presented in Table 3.1, collapsed across Experiments 1, 2 and 3. The two neutral film clips are also taken together in the Table, as 1 neutral film condition, since the results were the same as taken separate. Tukey pairwise comparisons confirmed that film clip “Sadness”, indeed induced more sadness than any other clip, as well as disgust and “Anxiety” induced more anxiety than any other clip, as well as fear. “Neutral1+2” never induced more positive emotions than the experimental conditions. For example, it did induce positivity, content, happiness and hope, but less than the experimental film conditions “Hope” and “Happy”. For the other emotions, it did not induce these emotions at all. Both film clips “Happy” and “Hope” induced more hope and happiness than any other film clips, as well as more content and enjoyment than any other film clip. This means that in Experiment 1 there is no clear distinction between the film conditions “Happy” and “Hope”, therefore analysis have been made with both film conditions together and separate. For Experiment 2 and 3 this is no problem, because only one of the film clips “Happy” or “Hope” is compared to a neutral and negative emotion (either anxiety or sadness). The original labels “Happy” and “Hope” are kept throughout the chapter to point to the content of the movie and intended manipulation. This manipulation check shows though, that the effects of both movies are similar, namely inducing the positive emotions: happiness, hope,
Table 3.2. Modal and mean self-reported emotion for film clips

<table>
<thead>
<tr>
<th>Emotion</th>
<th>Anxiety</th>
<th>Hope</th>
<th>Happy</th>
<th>Sad</th>
<th>Neutral 1+2</th>
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<tbody>
<tr>
<td><strong>Sadness</strong></td>
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<tr>
<td>mode</td>
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<td>1</td>
<td>1</td>
<td>7</td>
<td>1</td>
</tr>
<tr>
<td>mean (SD)</td>
<td>3.35 (1.86)</td>
<td>2.38 (1.94)</td>
<td>2.18 (1.69)</td>
<td>6.00 (2.59)</td>
<td>1.55 (1.04)</td>
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<tr>
<td><strong>Fear</strong></td>
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<tr>
<td>mode</td>
<td>6</td>
<td>1</td>
<td>1</td>
<td>1</td>
<td>1</td>
</tr>
<tr>
<td>mean (SD)</td>
<td>6.06 (1.86)</td>
<td>1.50 (1.47)</td>
<td>1.60 (0.81)</td>
<td>4.10 (2.67)</td>
<td>1.67 (1.49)</td>
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<td>mode</td>
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<td>1</td>
<td>1</td>
<td>1</td>
<td>1</td>
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<tr>
<td>mean (SD)</td>
<td>2.03 (1.76)</td>
<td>1.68 (1.46)</td>
<td>1.88 (1.54)</td>
<td>3.35 (2.16)</td>
<td>1.45 (0.86)</td>
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<td><strong>Content</strong></td>
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<tr>
<td>mean (SD)</td>
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<td>7.10 (1.52)</td>
<td>6.63 (1.82)</td>
<td>2.83 (2.16)</td>
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<td>2.75 (2.16)</td>
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<td>3.05 (2.12)</td>
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<td>7.28 (1.66)</td>
<td>2.48 (1.92)</td>
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<td>1</td>
<td>1</td>
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<td>1</td>
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<td>mean (SD)</td>
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<td>1.70 (1.49)</td>
<td>1.40 (0.84)</td>
<td>3.85 (2.53)</td>
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<td>6.95 (2.04)</td>
<td>6.93 (1.73)</td>
<td>1.90 (1.24)</td>
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<td><strong>Irritation</strong></td>
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<td>mode</td>
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<td>1</td>
<td>1</td>
<td>1</td>
<td>1</td>
</tr>
<tr>
<td>mean (SD)</td>
<td>4.10 (2.78)</td>
<td>2.38 (2.05)</td>
<td>2.55 (2.28)</td>
<td>4.15 (2.53)</td>
<td>3.58 (2.41)</td>
</tr>
<tr>
<td><strong>Hope</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>mode</td>
<td>1</td>
<td>6</td>
<td>6</td>
<td>1</td>
<td>6</td>
</tr>
<tr>
<td>mean (SD)</td>
<td>2.48 (1.59)</td>
<td>6.20 (2.00)</td>
<td>5.18 (2.26)</td>
<td>2.90 (1.88)</td>
<td>4.42 (2.32)</td>
</tr>
<tr>
<td><strong>Anger</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
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<tr>
<td>mode</td>
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<td>1</td>
<td>1</td>
<td>6</td>
<td>1</td>
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<tr>
<td>mean (SD)</td>
<td>3.08 (2.14)</td>
<td>1.55 (1.40)</td>
<td>1.53 (0.99)</td>
<td>5.65 (2.59)</td>
<td>1.60 (1.49)</td>
</tr>
<tr>
<td><strong>Pride</strong></td>
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<td></td>
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<tr>
<td>mode</td>
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<td>5</td>
<td>5</td>
<td>1</td>
<td>1</td>
</tr>
<tr>
<td>mean (SD)</td>
<td>2.30 (1.87)</td>
<td>4.73 (2.33)</td>
<td>3.98 (2.17)</td>
<td>2.03 (1.31)</td>
<td>3.35 (2.29)</td>
</tr>
<tr>
<td><strong>Negative</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>mode</td>
<td>6</td>
<td>1</td>
<td>1</td>
<td>5</td>
<td>1</td>
</tr>
<tr>
<td>mean (SD)</td>
<td>5.38 (2.44)</td>
<td>1.93 (1.83)</td>
<td>1.75 (1.43)</td>
<td>6.03 (2.30)</td>
<td>2.51 (1.89)</td>
</tr>
<tr>
<td><strong>Anxiety</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>mode</td>
<td>8</td>
<td>1</td>
<td>1</td>
<td>3</td>
<td>1</td>
</tr>
<tr>
<td>mean (SD)</td>
<td>6.55 (2.89)</td>
<td>1.63 (1.64)</td>
<td>1.43 (0.78)</td>
<td>4.55 (2.59)</td>
<td>1.61 (1.40)</td>
</tr>
</tbody>
</table>

Note: N= 40 for Anxiety, Hope, Happy, Sad; N=63 for Neutral 1+2. Ratings were made on a 10-point Likert Scale, ranging from 1 = non, to 10 = a great deal.
content, enjoyment and positivity. Therefore, one could also read the labels “Happy” and “Hope” as “Positive”.

Furthermore, the modal emotion reports were high for the targeted emotions (7, 8 and 9 on a 10-point scale), and were typically 1 for untargeted emotions. For the “Neutral” film clip the modal emotion reports were 1 for the negative emotions. The modal reports for the positive emotions were between 5 and 7, but always lower than the modal reports of “Happy” and “Hope”.

Experiment 1

Analyses have been made for the original 5 film conditions and for only 4 film conditions, where “Happy” and “Hope” are merged into 1 film condition “Positive”, based on the manipulation check. For both analyses, across all participants, the mean thought-action repertoire size, as indexed by the number of things participants wanted to do, was 7.66(SD = 3.87). The group differences in repertoire size were tested using a One-way ANOVA. Both for the 5 film conditions and 4 film conditions there was no significant main effect for film group. \( F(4, 96) = 1.57, p = .19. F(3, 97), p = .67. \) A priori contrasts (one-side t-tests with 0.10 alpha) confirmed that the two positive emotion films combined did not yield larger thought action repertoires than did the neutral films \( t(59) = -7.88, p = 0.217. \) The two negative films combined also did not yield larger thought action repertoires than the neutral film, \( t(59) = .104, p = 0.46. \)

![Figure 1. Thought-action repertoire size by original 5 film conditions](image-url)
Part II: Modelling Emotion Contagion and Emotion Recognition

Figure 3.2. Thought-action repertoire size by new film conditions based on manipulation check (original Happy and Hope film condition together as Positive emotion condition)

Table 3. Mean Number of Urges and Confidence Intervals for each Film Condition

<table>
<thead>
<tr>
<th>Film Condition</th>
<th>Mean Number of Urges</th>
<th>SD</th>
<th>Lower End 95% Confidence Interval</th>
<th>Higher End 95% Confidence Interval</th>
</tr>
</thead>
<tbody>
<tr>
<td>Neutral1</td>
<td>7.38</td>
<td>3.53</td>
<td>5.77</td>
<td>8.99</td>
</tr>
<tr>
<td>Anxiety</td>
<td>7.6</td>
<td>2.65</td>
<td>6.22</td>
<td>8.98</td>
</tr>
<tr>
<td>Hope</td>
<td>9.5</td>
<td>4.55</td>
<td>7.37</td>
<td>11.63</td>
</tr>
<tr>
<td>Happy</td>
<td>6.9</td>
<td>3.0</td>
<td>5.51</td>
<td>8.29</td>
</tr>
<tr>
<td>Positive</td>
<td>8.2</td>
<td>4.01</td>
<td>6.92</td>
<td>9.48</td>
</tr>
<tr>
<td>Sadness</td>
<td>6.95</td>
<td>4.70</td>
<td>4.75</td>
<td>9.15</td>
</tr>
</tbody>
</table>

The content of participant’s responses was explored as well, across the 4 film groups (“Happy” and “Hope” together in “Positive”). Two-tailed focused contrasts were used that compared the neutral film to each of the emotional film conditions. There were no differences found in the number of urges of the following categories: eat/drink, exercise/sport, outdoors/nature, play, be social, be antisocial, development/future plans. Increases of thought-action repertoire were found for categories travel, very positive feelings and doing something fun, but then in both positive and negative film conditions. Compared to participants who viewed the neutral film, participants both in the positive film condition and negative film condition reported more urges to travel/go on holiday. “Positive” vs “Neutral1”, t(58)= -2.12, p=0.038, “Anxiety” vs “Neutral1”, t(39)=-2.203, p=0.034. Compared to participants that watched a neutral movie, participants that watched a negative film reported to have more positive feelings or thoughts: “Anxiety” vs “Neutral1”, t(39)=-2.05,
p = 0.052, “Sadness” vs “Neutral1”, t(38)=2.11, p=0.041. Compared to a neutral film condition, participants that watched a negative film reported to have more urge to do something fun: “Sadness” vs “Neutral1”, t(39)=−2.57, p=0.014. Decreases in though action repertoire were found in the categories read and relaxation/sleep. In the positive film condition, compared to participants in the neutral condition, participants reported to want to do less fun: “Positive” vs “Neutral1” t(58)=2.42, p=.019. The negative film conditions did not differ from the neutral film condition. Compared to the neutral film condition, participants reported to want to do less relaxation/sleeping after watching a positive film: t(58)=2.71, p=.009. But also after watching a negative movie: “Anxiety” vs “Neutral1”, t(39)=1.87, p=0.07. In sum, both positive and negative film conditions increased the thought-action repertoire for the categories travel, very positive feelings and doing something fun. Thought-action-repertoires shrunk in the positive film condition for the categories read and relaxation/sleep. Positive or negative film conditions did not have effect on the increase or decrease of thought-action repertoires for the categories: eat/drink, exercise/sport, outdoors/nature, play, be social, be antisocial, development/future plans.

Experiment 2
Analyses have been made for the combined scores of the three Creativity Tests and for each test separate. Across all participants, the mean combined score of the Creativity Tests was 68.79 (SD=22.59). A One-Way ANOVA tested for group difference, no main effect for factor Film Group was found, F(58)=1.02, p = .368. Figure 3.3 presents mean combined creativity test scores for each Film Group and Table 3.4 shows all confidence intervals. Each creativity test was also analysed individually. Across all participants, the mean score of the Guilford Creativity Tests was 27.41 (SD=12.05). A One-Way ANOVA tested for group difference, no main effect for factor Film Group was found, F(58)=0.065, p = .937. Figure 3.4 presents mean Guilford creativity test scores for each Film Group. Across all participants, the mean score of the Wallas Creativity Tests was 41.03 (SD=15.78). A One-Way ANOVA tested for group difference, no main effect for factor Film Group was found, F(58)=.415, p = .662. Figure 3.5 presents mean Wallas creativity test scores for each Film Group. Across all participants, the mean score of the RAT Creativity Tests was 3.38 (SD=1.61). A One-Way ANOVA tested for group difference, no main effect for factor Film Group was found, F(58)=1.1, p = .340. Figure 3.5 presents mean Wallas creativity test scores for each Film Group. Through a priori contrast, no significant differences were found between the neutral film condition and the positive or negative film condition.
**Part II: Modelling Emotion Contagion and Emotion Recognition**

**Figure 3.** Combined Creativity Tests scores by emotion condition

**Table 4.** Mean Combined Creativity Scores and Confidence Intervals for each Film Condition

<table>
<thead>
<tr>
<th>Film Condition</th>
<th>Mean Combined Creativity Score</th>
<th>SD</th>
<th>Lower End 95% Confidence Interval</th>
<th>Higher End 95% Confidence Interval</th>
</tr>
</thead>
<tbody>
<tr>
<td>Neutral1</td>
<td>73.67</td>
<td>17.21</td>
<td>65.83</td>
<td>81.50</td>
</tr>
<tr>
<td>Anxiety</td>
<td>63.60</td>
<td>27.41</td>
<td>50.77</td>
<td>76.43</td>
</tr>
<tr>
<td>Hope</td>
<td>68.85</td>
<td>22.22</td>
<td>58.45</td>
<td>79.25</td>
</tr>
</tbody>
</table>

**Figure 3.4.** Guilford Creativity Test scores by emotion condition
Experiment 3

Analyses have been made for each of the three Memory Tests separate. Across all participants, the mean score of the GIST Memory Test was 3.75 (SD=1.05). A One-Way ANOVA tested for group difference, a main effect for factor Film Group was found, $F(57) = 11.97, p < 0.0001$. Figure 3.7 presents mean GIST memory test scores for each Film Group and Table 3.5 shows all confidence intervals. Post hoc Tukey pairwise comparisons with LSD correction showed that compared to the neutral film condition, participants watching a negative film condition were less good in recalling the GIST, “Neutral2” vs “Sad” $p < 0.0001$, but watching a positive film did not increase the GIST recall “Neutral2” vs “Happy”, $p = .934$. Furthermore, there is a significant difference in GIST recall between the two experimental conditions, “Happy” vs “Sad”, $p < 0.0001$. 
Part II: Modelling Emotion Contagion and Emotion Recognition

Figure 7. GIST memory scores by emotion condition

Table 5. Mean GIST Memory Scores and Confidence Intervals for each Film Condition

<table>
<thead>
<tr>
<th>Film Condition</th>
<th>Mean GIST Memory Score</th>
<th>SD</th>
<th>Lower End 95% Confidence Interval</th>
<th>Higher End 95% Confidence Interval</th>
</tr>
</thead>
<tbody>
<tr>
<td>Neutral2</td>
<td>4.10</td>
<td>.912</td>
<td>3.67</td>
<td>4.53</td>
</tr>
<tr>
<td>Happy</td>
<td>4.20</td>
<td>.834</td>
<td>3.81</td>
<td>4.59</td>
</tr>
<tr>
<td>Sad</td>
<td>2.95</td>
<td>.945</td>
<td>2.51</td>
<td>3.39</td>
</tr>
</tbody>
</table>

Across all participants, the mean score of the CENTRAL Memory Test was 2.95(SD=1.16). A One-Way ANOVA tested for group difference, a main effect for factor Film Group was found, $F(57)=15.09., p<0.0001$. Figure 3.8 presents mean CENTRAL memory test scores for each Film Group and Table 3.6 shows all confidence intervals. Post hoc Tukey pairwise comparisons showed that compared to the neutral film condition, participants watching a negative film condition were less good in recalling the CENTRAL aspects, “Neutral2” vs “Sad” $p=.041$, watching a positive film increased CENTRAL aspects memory “Neutral2” vs “Happy”, $p <.0001$. Furthermore, there is a significant difference in CENTRAL Memory aspects between the two experimental conditions, “Happy” vs “Sad”, $p=0.011$. 
Table 6. Mean CENTRAL Memory Scores and Confidence Intervals for each Film Condition

<table>
<thead>
<tr>
<th>Film Condition</th>
<th>Mean CENTRAL Memory Score</th>
<th>SD</th>
<th>Lower End 95% Confidence Interval</th>
<th>Higher End 95% Confidence Interval</th>
</tr>
</thead>
<tbody>
<tr>
<td>Neutral2</td>
<td>2.15</td>
<td>.23</td>
<td>1.66</td>
<td>2.64</td>
</tr>
<tr>
<td>Happy</td>
<td>3.80</td>
<td>.17</td>
<td>3.44</td>
<td>4.16</td>
</tr>
<tr>
<td>Sad</td>
<td>2.90</td>
<td>.23</td>
<td>2.42</td>
<td>3.38</td>
</tr>
</tbody>
</table>

Figure 8. CENTRAL memory scores by emotion condition

Figure 9. BACKGROUND memory scores by emotion condition
Table 7. Mean BACKGROUND Memory Scores and Confidence Intervals for each Film Condition

<table>
<thead>
<tr>
<th>Film Condition</th>
<th>Mean BACKGROUND Memory Score</th>
<th>SD</th>
<th>Lower End 95% Confidence Interval</th>
<th>Higher End 95% Confidence Interval</th>
</tr>
</thead>
<tbody>
<tr>
<td>Neutral2</td>
<td>1.65</td>
<td>.88</td>
<td>1.24</td>
<td>2.06</td>
</tr>
<tr>
<td>Happy</td>
<td>2.90</td>
<td>1.30</td>
<td>2.29</td>
<td>3.51</td>
</tr>
<tr>
<td>Sad</td>
<td>1.40</td>
<td>.88</td>
<td>.99</td>
<td>1.81</td>
</tr>
</tbody>
</table>

Across all participants, the mean score of the BACKGROUND Memory Test was 1.98 (SD=1.21). A One-Way ANOVA tested for group difference, a main effect for factor Film Group was found, $F(57)=12.04, p<0.0001$. Figure 3.9 presents mean BACKGROUND memory test scores for each Film Group and Table 3.7 shows all confidence intervals. Post hoc Tukey pairwise comparisons showed that compared to the neutral film condition, participants watching a positive film increased BACKGROUND aspects of memory “Neutral2” vs “Happy”, $p=0.001$. Furthermore, there is a significant difference in BACKGROUND Memory aspects between the two experimental conditions, “Happy” vs “Sad”, $p<0.0001$. Watching a negative film did not increase or decrease the participant’s performance in the BACKGROUND Memory aspects, “Neutral2” vs “Sad”, $p=.727$. In sum, compared to a neutral film, watching a negative film decreases GIST and CENTRAL aspects of memory and watching a positive film, increased CENTRAL and BACKGROUND aspects of memory.

3.4 Discussion

Based on Frederickson’s broaden-and-build theory (Frederickson 1998, 2001), the present study examined the effect of positive and negative emotions, in comparison to a neutral state, on a person’s thought-action repertoires, creativity levels and memory. Research on Fredrickson’s (1998, 2002, 2005) broaden and build theory is limited. Therefore, the current project is a great contribution to the existing literature. The goals of this research were to replicate the results in Frederickson & Branigan (2005), namely that positive emotions broaden people’s action urges and negative emotions narrow their action urges, in comparison to a neutral state, and to expand on the research by Frederickson by testing the broaden-and-build theory in two new cognitive abilities: creativity and memory. A manipulation check confirmed that the intended emotions were induced in the participants.

In Experiment 1 the effect of hope, happiness, sadness and anxiety, in comparison to a neutral state, on a person’s thought action repertoire were investigated in the same way as in Frederickson and Branigan (2005). The
emotions were induced through movie clips and the number of action urges were gathered from the participants via a verbal open-ended Twenty Statements Test. However, no effect of emotions on the number of urges was found in experiment 1. The hypothesis that positive emotions broaden a person’s thought-action repertoires and that negative emotions narrow them, was not supported. The analysis of the content of participant’s responses also did not support the broaden-and-build theory. Unlike Frederickson and Branigan (2005), there was no effect of positive or negative emotions on the proportions scores of the participants in any of the categories: eat/drink, exercise/sport, outdoors/nature, play, be social, be antisocial, development/future plans. Increases of thought-action repertoire were found for categories travel, very positive feelings and doing something fun, but then in both positive as negative film conditions. Decreases in thought action repertoire were found in the categories read and in relaxation/sleep in the positive film condition. All these findings do not support the broaden-and-build theory.

In Experiment 2, the effect of anxiety and hope (a negative and positive emotion) compared to a neutral emotion, on people’s creativity levels, was investigated. The emotions were induced via movie clips and the creativity was measured via a combination of three creativity tests that measured divergent and convergent thinking. Again, no effect of hope and anxiety, compared to a neutral state, on participants creativity levels was found and therefore no support was found for the broaden-and-build theory.

In Experiment 3, the effect of happiness and sadness, in comparison to a neutral state, on gist, central and background memory was investigated. It was expected that, according to the broaden-and-build theory, the positive emotion ‘happiness’ will broaden the attention and therefore cause an improvement in the gist, central and background memory. The negative emotion ‘sadness’ was expected to cause a narrowing of attention according to the broaden-and-build theory, weapon focus effect and cue utilisation theory (Easterbrook, 1959) and therefore decreasing the background memory performance, but increasing the gist and central memory aspects. The results demonstrated that compared to a neutral state, watching a negative film decreases gist and central aspects of memory and watching a positive film, increased central and background aspects of memory. These results indicate support for the broaden-and-build theory, but modest support for the weapon focus effect and cue utilisation theory. Although happiness increased central and background aspects of memory, it had no effect on gist memory, which was also expected. Also, sadness did decrease central aspects of memory, it was expected to increase gist memory instead of decreasing it. Also sadness was expected to have a decreasing effect on background memory, but it had no
effect. Overall, there was a broadening effect of happiness on central and background memory and a narrowing effect of sadness on gist and central memory, which do support the broaden-and-build theory.

What was interesting in experiment 1, is that not the number of action urges corresponded to the results of Frederickson and Branigan (2005), but the content did. Almost all categories of Frederickson and Branigan (2005) were found in the current research as well. The contradictory finding, that in the current research there was no effect of positive or negative emotions on the number of action urges could be explained by the fact that the participants regulated their emotions during answering the Twenty Statements Test. Although it was (indirectly) instructed to not regulate your emotions, but by feeling how you do right now, state all the things you would like to do. By listening to the recordings to write out the answers, it was found that participants were induced with the correct emotion, but regulated their emotion while answering the Twenty Statements test. Examples are: “Well I would like to do fun things now, to forget what I just saw” or “I would like to listen to music to defer my attention from how I feel right now”. In a future experiment it would be necessary to instruct the participants directly, to not regulate their feelings and action urges. It could still be possible that there was an effect of positive or negative emotions on the number of action urges, but that it was hidden due to emotion regulation.

Furthermore, in the current research the effects of hope, happiness, anxiety and sadness, compared to a neutral state, were investigated, while in Frederickson and Branigan (2005) the effects of amusement, contentment, serenity, anger, disgust, fear and anxiety were investigated. It could be that the results of Frederickson and Branigan (2005) were not replicated because different emotions were used in the current research. This could also account for the results in experiment 2. Perhaps hope and anxiety do not have an effect on creativity levels, but other emotions do. Another difference between the current research and that of Frederickson and Branigan (2005), was that in the current research the participants stated their action urges verbally instead of written. Perhaps talking itself, or communicating to the experimentator altered the number and/or the content of the action urges. Nevertheless, a great strength of the current study was that the participants performed the experiment on their own; the experimenter and the participant were located in different rooms throughout the experiment. This way participants were able to concentrate better on their emotions as it may have made them more comfortable and less pressured.

Another explanation to why there was no effect found of positive and negative emotions on people’s thought action repertoires and creativity levels, could lie in the small number of participants per condition (20) in both the
current research and in Frederickson and Branigan (2005). Only with a large effect size, like Cohen’s $d = 1$ and enough power, 20 participants per condition would be enough to find the results as in Frederickson and Branigan (2005). However, one should still be cautious with the findings of the current research and that of Frederickson and Branigan (2005). Follow-up experiments with more participants per condition would therefore be advisable.

For all three experiments it holds that more research is necessary. Most advisable are the induction of exactly the same emotions, but also new emotions and to increase the number of participants per condition. The induction of movie clips seems to be successful, because in both studies, it correctly induced the intended emotions in the participants. The current research can therefore be seen as a mix of confirmation and rejection of the broaden-and-build theory that needs more research to point in just one of these two directions.

References


Kowalczyk, W. and Wal, C.N. van der. See Chapter 4 of this book


Chapter 4 - Detecting changing emotions in human speech by machine and humans

Wojtek Kowalczyk and C. Natalie van der Wal

Abstract. The goals of this research were: (1) to develop a system that will automatically measure changes in the emotional state of a speaker, by analyzing his/her voice, (2) to validate this system with a controlled experiment and (3) to visualize the results to the speaker in 2-d space. Natural (non-acted) human speech of 77 (Dutch) speakers was collected and manually splitted into meaningful speech units. Three recordings per speaker were collected, in which he/she was in a positive, neutral and negative state. For each recording, the speakers rated 16 emotional states on a 10-point Likert Scale. The Random Forest algorithm was applied to 207 speech features that were extracted from recordings to qualify (classification) and quantify (regression) the changes in speaker’s emotional state. Results showed that predicting the direction of change of emotions and predicting the change of intensity, measured by Mean Squared Error, can be done better than the baseline (the most frequent class label and the mean value of change, respectively). Moreover, it turned out that changes in negative emotions are more predictable than changes in positive emotions. A controlled experiment investigated the difference in human and machine performance on judging the emotional states in one’s own voice and that of another. Results showed that humans performed worse than the algorithm in the detection and regression problems. Humans, just like the machine algorithm, were better in detecting changing emotions in negative than positive emotions. Finally, PCA results showed a validation of dimensional emotion theories in the emotional data and to be a promising technique for visualizing the data in the envisioned application.

Part of this chapter will appear as:
4.1 Introduction
Imagine that your telephone can continuously recognise the emotions you feel, through classifying acoustic features in your voice. The possibilities would be endless. You could use your phone to get insights in your own emotional well-being. Your telephone could be your therapist by listening to your voice and assess your emotional well-being. It could perhaps prevent you from depression by contacting your friends or a professional to help you or give you assignments to feel better. Your phone could also be a social coach, giving you lessons and ratings in how to use your voice to come across positive and enthusiastic instead of lethargic and negative. The current research stems from this vision.

The field of emotion recognition by machines is called affective sensing [15]. Besides the envisioned application indicated above, many other applications of emotion recognition are possible, for example emotion recognition in speech is used in call centers to detect anger in the voice of employees and to give them appropriate feedback,[19]. Emotion recognition is useful in real-time conversations with embodied agents in human computer interaction, for example in computer games, but also in (web)applications with virtual therapists. In the multidisciplinary research of emotion, many definitions of emotions exist. In this chapter, emotion is considered as elicited by a particular stimulus and relatively intense and short lived [8].

Many approaches and techniques are available in emotion recognition research. Emotional expression can be investigated in many different modalities, like gesture, posture, facial expression and speech; e.g. [4], [13], [15], [18], [19]. In [15], the authors claim that affective sensing systems can recognize emotions in human voices and facial expressions better, if semantic features are analyzed as well, besides the standard analysis of sound patterns (like prosody and energy levels), and pattern matching or statistical machine learning techniques in facial expressions. Besides adding semantics to the emotion recognition process, it seems that multimodal emotion recognition gains higher accuracy than uni-modal emotion recognition. For example in [4] it is shown how emotion recognition through the multiple modalities: facial expressions, body gesture and speech, produces higher accuracy than through any of the single modalities. There are still big steps to be made in research in uni-modal emotion recognition, for example in speech recognition. In [19], the main challenges in automatic emotion recognition from speech are discussed; how to segment audio files, how to extract the relevant features in these speech units and how to classify and train databases with emotional speech. In [1] the authors go deeper into one of these issues: which features in speech are the most important for high accuracy in emotion recognition systems? All
of these emotion recognition systems analyze individual uni- or multimodal emotional fragments of human speech, facial expressions or body gestures.

In this chapter, the focus is on a single modality, namely speech. One reason for this is that speech is easy to capture/collect. A second reason is that it is easier to process, compared to images/video, which is important for the envisioned application that uses a smart phone processor.

The ultimate goal is to develop a system that will automatically measure changes in the emotional state of a speaker, by analyzing his/her voice and show the results to the speaker. To achieve this goal the following research questions are addressed: (1) How accurate can the designed intelligent agent predict if a certain emotion in human speech is becoming weaker or stronger? (2) How accurate can it predict how substantial the change is? (3) Do humans perform better or worse than the machine algorithm? (4) How can the emotional states be visualized to the speaker?

The conventional approach of estimation of emotion consists of three steps: 1. Collect human speech as training data, 2. Extract speech features, 3. Use a machine-learning algorithm or statistical analysis to find relations between emotion and speech features, see [12] or [1]. The presented research followed a common approach that is used in pattern classification, [5], which involves the following steps: capturing data from sensors (in our case: microphones), data segmentation (in our case: manual splitting or recordings into meaningful pieces and labelling them), feature extraction (converting each recording into a vector of features of fixed length) and developing a classification or regression model (we used Random Forests). Random Forests were used to address a classification problem (out of 2 recordings, which one has the highest emotional value?) and a regression problem (given 2 recordings, estimate the difference in each emotional state).

The paper is organized as follows: in Section 4.2 the main steps of our approach to the problem are explained: the data capturing, data segmentation, feature extraction and data modelling. Section 4.3 describes the results of the machine learning algorithm. Section 4.4 shows the results of human performance on the same task. Section 4.5 addresses the problem of visualising the multidimensional emotional data in 2-d space. Section 4.6 shows the results of the validation experiments. Finally, Section 4.7 interprets the results and in Section 4.8, challenges, possible extensions and applications of this research are discussed.

4.2 Method

In the current research the standard approach that is used in pattern recognition was followed, [5]: capturing data from sensors (in this case: microphones), data segmentation (in this case: manual splitting or recordings
into meaningful pieces and labelling them), feature extraction (converting each recording into a vector of features of fixed length), preparation of training sets, developing classification and regression models.

In the current experiments, Random Forests were used, [2], [10], for their superior accuracy, good generalization properties and ease of training. An alternative method to Random Forests could be Support Vector Machines (SVM) with some well chosen kernel functions, [17]. However, algorithms for training SVM are very sensitive to the choice of learning parameters and are computationally more demanding than Random Forests.

4.2.1 Data Collection

The speech samples used in this research were collected from 77 participants (Dutch university students and employees, 44.2% women, mean age: 26.77 years) during a laboratory study in which the participants were induced with positive, neutral or negative emotions. Participants were tested on the effect of emotion on different cognitive capabilities, by watching a 5-minute movie that induced a certain emotion and afterwards performing a verbal test that measured their creativity, attention or action urges. The speech of the participants was recorded with a ZOOM H1 voice recorder, through a clip-on microphone, with the automatic gain control on. Participants were informed that their speech was recorded during the experiment, so that the researcher could write out their answers afterwards. Participants had no clue that their speech was recorded for the purpose of emotion recognition by a machine. In this way, naturally occurring speech was collected. This is beneficial for this study, because it does not have the pitfalls of acted emotional speech. Acted speech elicits how emotions should be portrayed, not necessarily how they were portrayed. Also, acted emotions do not emerge in the body and mind of the individual as naturally occurring emotions do.

Another advantage of this data collection method is that the participants own ratings of their emotions were collected. Each of the 77 participants recorded, in 3 independent sessions, a short message (containing their name, age and the city of residence), while being in one of the 3 emotional states: "neutral" (entering the lab), "positive" (after watching a short "positive" movie), and "negative" (after watching a short "negative" movie). After their recording, each subject rated his/her emotional states on an Emotion Report Form containing the following 16 emotions: sadness, fear, shame, contentment, guilt, happiness, disgust, despair, positivity, enjoyment, irritation, hope, anger, pride, negativity, anxiety. Ratings were made on a 10-point Likert scale (1 = none, 10 = a great deal).
4.2.2 Data segmentation

The speech units were cut manually, starting exactly at the first phoneme spoken by the subject and ending directly after the last phoneme was spoken; periods of silence at the beginning and at the end of each recording were manually removed. As in realistic speech databases, the word itself is normally not the optimal emotion unit to be processed, the speech units collected in this research consist of several words. Each audio segmentation represents a unit that is representative for a positive or negative emotion. The name-age-city units establish a syntactically/semantically meaningful unit, in which we assume the felt emotion can be expressed easily by the participant, because he/she can identify him/herself with the semantic meaning of the words (and even with the sounds of the letters/words). The units differ in length for each subject, varying from 2 to 8 seconds. Each speech recording, originally stored in a wav format (stereo, 44.100 Hz frequency sampling), was converted into a single vector of numbers (signals from the two channels were combined into one: \( s_{\text{mono}} = (s_{\text{left}} + s_{\text{right}})/2 \)) and stored in Matlab.

Table 4.1. All 207 speech features used by the classification algorithm

<table>
<thead>
<tr>
<th>22 Speech Properties</th>
<th>9 Aggregates for each Speech Property</th>
</tr>
</thead>
<tbody>
<tr>
<td>F0 (Fundamental Frequency)</td>
<td>Mean</td>
</tr>
<tr>
<td>I (Sound Intensity, measured on the logarithmic scale)</td>
<td>Median</td>
</tr>
<tr>
<td>E (Sound Energy, measured in sound units)</td>
<td>Standard deviation</td>
</tr>
<tr>
<td>F1, F2, F3 (first 3 formants)</td>
<td>Skewness</td>
</tr>
<tr>
<td>B1, B2, B3 (bandwidth of first 3 formants)</td>
<td>Kurtosis</td>
</tr>
<tr>
<td>MFCC0-MFCC12 (13 Mel Frequency Cepstral Coefficients)</td>
<td>Q1 (mean of the smallest 20% of values)</td>
</tr>
<tr>
<td>SR (speech restarts)</td>
<td>Q5 (mean of the biggest 80% of values)</td>
</tr>
<tr>
<td></td>
<td>Shimmer (period to period variability)</td>
</tr>
<tr>
<td></td>
<td>Rise (percentage of times next value is bigger than the previous one)</td>
</tr>
</tbody>
</table>

4.2.3 Feature extraction

In order to apply any classification or regression algorithm to our recordings, each recording had to be converted to a vector of fixed length of sound features. It was difficult to say beforehand, which features would be most successful. Therefore almost all features that could be found in the available literature on analysing affective speech: [8], [1], [9], [11], [6], [3], [10], [7], were used. These features were calculated in two steps:
(1) Each recording was split into a sequence of short segments (10 milliseconds long), and a number of procedures were applied to each segment to calculate, among others, features like: fundamental frequency, energy, formants, cepstral coefficients.

(2) The values of the computed features were aggregated over the duration of the whole recording. The aggregates included mean, median, standard deviation, skewness.

The following table provides a complete overview of speech properties and aggregates that were used in the current experiments.

### 4.2.4 Training sets
After calculating all features for each recording, the final training set was prepared for developing classifiers or regression models. The following 2 problems were addressed:

**Classification**: Develop, for each of the 16 emotional states, a classification procedure, which, when applied to two recordings S1 and S2 will determine if the emotional state in S2 is "more present" than in S1 (has higher intensity value).

**Regression**: Develop, for each of the 16 emotional states, a regression procedure, which, when applied to two recordings S1 and S2 will estimate the difference of the intensity of the emotional state between S1 and S2.

Additionally, it was assumed that both recordings, S1 and S2, are coming from the same speaker and the input for the classification and regression procedure consists of the differences between feature vectors of S1 and S2, and not the original values. In other words, the change in emotional state has to be predicted from the change in feature vectors. The main reason for this assumption was caused by the scarcity of data: for each subject there were only 3 recordings and (big) interpersonal differences in speech features would dominate the subtle changes that reflect emotional states.

The training set was constructed as follows. Let S1, S2, S3 denote 3 recordings of the same subject. This triplet leads to 3 input vectors: S1-S2, S1-S3, S2-S3, and the corresponding output values: E1-E2, E1-E3, E2-E3 (in the regression task), or +1 or -1 (in the classification task), depending on the sign of the difference (cases where the difference was 0 were ignored). In total, the training set used for developing our regression and classification models had 225 records.
4.2.5 Modelling data with Random Forests

The concept of Random Forests was introduced by Leo Breiman in 2001 [2], and since then it became one of the most prominent technique for solving classification and regression problems [5]. The key idea behind this technique is a construction of many (hundreds) of de-correlated classification or regression trees and then aggregating their predictions. This leads to models with very good accuracy. The construction of a random forest of K trees for a set on N records is as follows:

Repeat steps (1) and (2) K times to develop K trees:
(1) draw a random sample of N records (with replacement) from the available data,
(2) develop a classification or regression tree for the data sample in the following way: (a) whenever a splitting attribute has to be chosen, consider all possible attributes and select at random one of the top L best attributes,
(b) whenever a node covers M (or less) records don't split it anymore.

When a Random Forest is applied to new data, outputs of all trees are either averaged (in case of regression), or the most frequent output label is chosen as a result (in case of classification). The Random Forest procedure involves 3 parameters: the number of trees to be developed, K, the number of best splitting attributes L, and the limit on the leaf size, M. Usually, the values of these 3 parameters are established experimentally with help plots such as the one presented in Figure 4.1. This figure represents the evolution of errors of 6 families of trees that are developed for the leaf size limit set to 1, 2, ..., 6 and L=50. It can be seen that M=4 and K=150-200 are the best parameters. In practice, the choice of value of K (the number of trees) is not critical: it has to be sufficiently big and further increase of this value has no impact on the tree accuracy. In this case, K was set to K=200. The optimal value of L was determined experimentally, by trying values L=25, 50, 75, 100; the best results were achieved for L=75. Finally, the choice of the minimal number of records in a leaf, M, was most difficult: it strongly depends on the emotional state that we wanted to model (different states needed different values of M). To choose this value, the following heuristic was used. For each emotion, we 6 values of M (1, 2, ..., 6) were tried, choosing the one that was best (had smallest average error) in the interval of 150-200 trees.

To avoid data overfitting out-of-bag error estimates were used, as described in [5]. These estimates are computed as follows. Each tree from a random forest is trained on a sample of data (a "bag"). Because data is sampled with replacement, some records are not used in the training (they are "out-of-bag") so they can be used as a test sample to estimate the accuracy of the
trained tree. Clearly, each tree is trained and tested on a different sample, therefore the average accuracy of all trees, measured on "out-of-bag" samples, gives a very reliable estimate of the true accuracy of the random forest.

![Image](image.png)

**Figure 4.1.** The evolution of errors of 6 families of trees

### 4.3 Results

The results of the experiments are summarised in Tables 4.2 and 4.3. In case of classification models, the error was measured by the percentage of misclassified cases. This error was then compared to the baseline error: the error made by the base classifier that always predicts the most frequent category. In case of regression models, the error measure was the Mean Squared Error, MSE. The baseline model was defined as a constant function equal to the mean value of the predicted variable.

Finally, the Relative Error Reduction (RER) was calculated which is defined as the ratio (BaselineError-ModelError)/BaselineError.
Table 4.2. Results of the classification problem. Error is measured by the ratio of misclassified records (misclassification rate).

<table>
<thead>
<tr>
<th>Emotion</th>
<th>Baseline Error</th>
<th>Model Error</th>
<th>Relative Error Reduction</th>
</tr>
</thead>
<tbody>
<tr>
<td>sadness</td>
<td>0.4024</td>
<td>0.3491</td>
<td>13.24%</td>
</tr>
<tr>
<td>fear</td>
<td>0.3924</td>
<td>0.2975</td>
<td>24.19%</td>
</tr>
<tr>
<td>shame</td>
<td>0.4397</td>
<td>0.2414</td>
<td>45.10%</td>
</tr>
<tr>
<td>content</td>
<td>0.3109</td>
<td>0.3057</td>
<td>1.67%</td>
</tr>
<tr>
<td>guilt</td>
<td>0.3578</td>
<td>0.3853</td>
<td>-7.69%</td>
</tr>
<tr>
<td>happiness</td>
<td>0.4341</td>
<td>0.4439</td>
<td>-2.25%</td>
</tr>
<tr>
<td>disgust</td>
<td>0.2628</td>
<td>0.2564</td>
<td>2.44%</td>
</tr>
<tr>
<td>despair</td>
<td>0.3889</td>
<td>0.3175</td>
<td>18.37%</td>
</tr>
<tr>
<td>positivity</td>
<td>0.3418</td>
<td>0.3316</td>
<td>2.99%</td>
</tr>
<tr>
<td>enjoyment</td>
<td>0.399</td>
<td>0.3695</td>
<td>7.41%</td>
</tr>
<tr>
<td>irritation</td>
<td>0.3113</td>
<td>0.2914</td>
<td>6.38%</td>
</tr>
<tr>
<td>hope</td>
<td>0.3242</td>
<td>0.3626</td>
<td>-11.86%</td>
</tr>
<tr>
<td>anger</td>
<td>0.3514</td>
<td>0.3514</td>
<td>0.00%</td>
</tr>
<tr>
<td>pride</td>
<td>0.2442</td>
<td>0.2558</td>
<td>-4.76%</td>
</tr>
<tr>
<td>negativity</td>
<td>0.3714</td>
<td>0.3429</td>
<td>7.69%</td>
</tr>
<tr>
<td>anxiety</td>
<td>0.3168</td>
<td>0.2857</td>
<td>9.80%</td>
</tr>
</tbody>
</table>

Table 4.3. Results of the regression problem. The Mean Squared Error measure is used (MSE).

<table>
<thead>
<tr>
<th>Emotion</th>
<th>Baseline Error</th>
<th>Model Error</th>
<th>Relative Error Reduction</th>
</tr>
</thead>
<tbody>
<tr>
<td>sadness</td>
<td>9.1392</td>
<td>8.5159</td>
<td>6.82%</td>
</tr>
<tr>
<td>fear</td>
<td>12.1157</td>
<td>10.2778</td>
<td>15.17%</td>
</tr>
<tr>
<td>shame</td>
<td>2.7825</td>
<td>2.4361</td>
<td>12.45%</td>
</tr>
<tr>
<td>content</td>
<td>12.7282</td>
<td>11.6326</td>
<td>8.61%</td>
</tr>
<tr>
<td>guilt</td>
<td>4.2478</td>
<td>4.0052</td>
<td>5.71%</td>
</tr>
<tr>
<td>happiness</td>
<td>15.7575</td>
<td>14.2149</td>
<td>9.79%</td>
</tr>
<tr>
<td>disgust</td>
<td>16.5909</td>
<td>14.4593</td>
<td>12.85%</td>
</tr>
<tr>
<td>despair</td>
<td>7.5872</td>
<td>6.7577</td>
<td>10.93%</td>
</tr>
<tr>
<td>positivity</td>
<td>15.3961</td>
<td>14.0813</td>
<td>8.54%</td>
</tr>
<tr>
<td>enjoyment</td>
<td>17.1388</td>
<td>16.2514</td>
<td>5.18%</td>
</tr>
<tr>
<td>irritation</td>
<td>8.2867</td>
<td>7.2742</td>
<td>12.22%</td>
</tr>
<tr>
<td>hope</td>
<td>10.0526</td>
<td>9.4538</td>
<td>5.96%</td>
</tr>
<tr>
<td>anger</td>
<td>10.4548</td>
<td>9.5458</td>
<td>8.69%</td>
</tr>
<tr>
<td>pride</td>
<td>7.8706</td>
<td>7.4964</td>
<td>4.75%</td>
</tr>
<tr>
<td>negativity</td>
<td>13.6128</td>
<td>11.5905</td>
<td>14.86%</td>
</tr>
<tr>
<td>anxiety</td>
<td>15.0084</td>
<td>13.1273</td>
<td>12.53%</td>
</tr>
</tbody>
</table>
4.3.1 Most Important Features
The Random Forest algorithm provides a powerful mechanism for measuring the importance of attributes that are used in the modelling process [5]. To measure the importance of an attribute, its values are permuted and the original accuracy of the model (measured on out-of-bag samples) is compared to the accuracy of the model on the modified data (on the same out-of-bag samples). The observed difference between both accuracies is strongly related to the importance of the attribute: the bigger the difference the more important the attribute.

With the help of this method, the importance of each attribute was found and calculated, for each emotion. Due to lack of space only the most frequent attributes that were used by Random Forests are listed. More precisely, for each model, the five most important attributes were listed, all 32 lists (16 for classification and 16 for regression) were concatenated and frequencies of the attributes on the list were computed. The most frequent attributes are listed in Table 4.4. The identification of the most informative features has 3 objectives: (1) verification of our findings with the existing literature, (2) simplification of the implementation of the automated system for monitoring emotions, (3) better understanding of the emotion-speech relation.

<table>
<thead>
<tr>
<th>Most important attributes</th>
<th>Frequency</th>
</tr>
</thead>
<tbody>
<tr>
<td>M2std: the standard deviation of the 2nd cepstral coefficient</td>
<td>38 times</td>
</tr>
<tr>
<td>M6mean: the mean value of the 6th cepstral coefficient</td>
<td>16 times</td>
</tr>
<tr>
<td>PU: the period to period variability (shimmer) of speech energy</td>
<td>12 times</td>
</tr>
<tr>
<td>I: the speech intensity</td>
<td>12 times</td>
</tr>
<tr>
<td>M6: the 6th cepstral coefficient</td>
<td>12 times</td>
</tr>
</tbody>
</table>

4 Validation Experiment
In this section, the results of the controlled experiment, in which humans perform the same task as the machine algorithm in the previous section, are presented. The following research questions will be examined:

1. Are humans better or worse than the machine algorithm in the classification of emotions? (out of 2 recordings, which one has the highest emotional value?).
2. Are humans better or worse than the machine algorithm in the regression problem? (Given 2 recordings, estimate the change of each emotional state).
3. Are humans better in detecting changing emotions in negative than positive emotions, like the machine algorithm?
(4) Are humans better in predicting changing emotions in their own voice than somebody else’s voice?
(5) Are humans better in detecting changing emotions when they can also use semantic cues in the audio files, besides the acoustic cues?
(6) Are humans better in detecting changing emotions when they learn how the speaker rated his own feelings than when they did not learn this?

For questions 1 and 2, the machine algorithm is expected to perform better than humans, because humans cannot find semantic cues in these recordings. Also, the acoustic emotional cues are difficult for humans to hear, because the recordings sound like the speakers are repeating a memorised sentence, a bit monotonic/non-emotional. For question 3, there is no expectation beforehand. Regarding question 4, it is expected that humans perform better in emotion recognition in their own voice, because we tend to know our own voice better than a stranger’s voice. For question 5, it is expected that humans perform better when they can also use semantic cues in the recordings, like “I would like to yell and scream” or “I would like to jump for joy”. Finally, regarding question 6, it is expected that humans perform better when they learn by seeing the speaker’s own emotional ratings for one recording, than when they do not.

4.4.1 Method

Participants
Experiment 1. The total number of participants (a subset of the total of participants of experiment 1) was 12 university students and employees (58.3% women, average age 31.9 years).

Experiment 2, 3, 4 and 5. The total number of participants was 14 university students and employees (50% women, average age 31.6 years).

Participants for all experiments were randomly selected from the subject pool of 80 participants that entered the original experiment 5 months earlier in which their voices were recorded. Each participant received a chocolate bar as reward.

Materials
Written. Emotional experiences were assessed using an Emotion Report Form, based on the Geneva Appraisal Questionnaire (GAQ, 2002) and the emotion report form used by Frederickson and colleagues. (Fredrickson et al. 2000). Participants rated how much they thought the speaker was feeling each of the following 16 emotions: sadness, fear, shame, contentment, guilt, happiness, disgust, despair, positivity, enjoyment, irritation, hope, anger, pride,
negativity, anxiety. Ratings were made on a 10-point Likert scale (1 = none, 10 = a great deal).

**Auditory.** 168 audio files served as the experimental manipulation in this research.

In the original experiment, 5 months earlier, speech was collected from the participants. 4 different types of audio files were manually split. The first type, in which the participant stated his/her name, age and city of residence, was used as the training and test sets of the emotion recognition system in the previous section. In the current validation experiment three other types of audio files were used as well. The reason for this was, to be able to compare human performance on audio files with and without semantic information. The four types of audio files are explained in Table 4.5. Especially in the “TAR” and “CR” files, the participants could find semantic cues to how the speaker feels at that moment, either positive or negative. (For example, if a person felt angry, he/she would state he/she would like to fight and yell, and when a person was happy, he/she would state he/she would like to dance and smile.)

**Table 4.5.** The 4 types of audio files used in the validation experiment

<table>
<thead>
<tr>
<th>Type of Audio File</th>
<th>Explanation</th>
</tr>
</thead>
<tbody>
<tr>
<td>“NAC” (Name-Age-City)</td>
<td>The speaker states his name, age and city of residence</td>
</tr>
<tr>
<td>“TAR” (Thought Action Repertoire)</td>
<td>The speaker states all the things he/she would like to do right now (based on his/her current emotions). For example: “I would like to go surfing, snowboarding, uhm...go out with friends, ...uhm and drink a cup of coffee”</td>
</tr>
<tr>
<td>“MEM” (Memory)</td>
<td>The speaker reads out the first question of the memory task and the answer. For example: “What colour is the tie of Mr. Bean? The answer is purple/green.”</td>
</tr>
<tr>
<td>“CR” (Creativity)</td>
<td>The speaker states all things he can think of, one can do with a newspaper. For example “Uhm..., you can fold it into a boat, you can kill a fly with it, uhm..., you can recycle it, uhm...”</td>
</tr>
</tbody>
</table>

Each participant listened to a total of 12 speech recordings: 4 recordings of themselves and 8 recordings of two other persons. There were three conditions in this experiment: “Self”, “Other-without-learning” and “Other-with-learning”, explained in Table 4.6. Each participant performed each condition. For all participants, the orders of the three conditions and of the four audio files in each condition were randomised, to control for order effects.
Table 4.6. The 3 conditions of the experiment

<table>
<thead>
<tr>
<th>Condition</th>
<th>Explanation</th>
</tr>
</thead>
<tbody>
<tr>
<td>“Self”</td>
<td>Participants listened to 4 speech recordings of themselves, recorded in the laboratory study they entered 5 months ago.</td>
</tr>
<tr>
<td>“Other-without-learning”</td>
<td>Participants listened to 4 speech recordings of another person, recorded during the same laboratory study they entered, 5 months ago.</td>
</tr>
<tr>
<td>“Other-with-learning”</td>
<td>Participants listened to 4 speech recordings of another person, recorded during the same laboratory study they entered, 5 months ago. During the first recording, the participant could study the Emotion Report Form filled in by the speaker (to learn to detect the right emotional state in the voice of the speaker)</td>
</tr>
</tbody>
</table>

**Dependent Measure**

The ratings of humans on changing emotions in the speaker were made on the Emotion Report Form, on which 16 emotions could be rated: sadness, fear, shame, contentment, guilt, happiness, disgust, despair, positivity, enjoyment, irritation, hope, anger, pride, negativity, anxiety. Ratings were made on a 10-point Likert scale (1 = none, 10 = a great deal). In the original experiment, the speakers would have filled in the same statements on an Emotion Report Form on the same 10-point Likert scale. From these ratings, different calculations were made to answer the different research questions. For research questions 1, 2 and 3 (to compare human and machine performance in the same way) the participants’ ratings of subsequent audio files of the same speaker were compared in the same way as recordings S1-S2, S2-S3 and S3-S1 were compared in the previous section. The only difference is that in this experiment the orders of the files were preset, namely 111 different orders in experiment 2 and 20 different orders in experiment 1. The errors were calculated in the same way as the classification and regression problems of the machine algorithm. For the classification problem, the error was measured by the percentage of misclassified cases. This error was then compared to the baseline error: the error made by the base classifier that always predicts the most frequent category. In case of regression models, the error measure was the Mean Squared Error, MSE. The baseline model was defined as a constant function equal to the mean value of the predicted variable. For both classification and regression problems, the Relative Error Reduction (RER) was defined as the ratio \((\text{BaselineError - ModelError})/\text{BaselineError}\). To answer research questions 4 (Do humans detect changing emotions better in their own voice than another person’s...
voice), the human performances of condition “Self” was compared to conditions “Other-without-learning” and “Other-with-learning” together in experiment 4. To answer research question 5 (Do humans perform better when using semantic cues + acoustic cues compared to only acoustic cues?), the human performances on the “NAC” audio files were compared to the performances on the “MEM”, “TAR” and “CR” audio files together in experiment 5. Finally, to answer research question 6 (Do humans perform better in the ‘learning’ condition than the ‘non-learning’ condition?), the human performances on the condition “Other-with-learning” was compared to “Other-without-learning” in experiment 6. For research question 4, 5, and 6, the average ratings on each emotional state, per stated condition, were compared.

**Procedure**

Participants were tested individually. On arrival, they were seated behind a desk and provided their informed consent. A laptop with headphones was located in front of the participant, next to the written material: the Emotion Report Forms and the instruction of the experiment. After reading the instructions, the participant would use the headphone to listen to 12 recordings in the order instructed to him. Each participant would listen to 4 recordings of himself, and 8 recordings of 2 other persons (4 each). After listening to each recording, the participant reported the emotional states of the speaker on an Emotion Report Form. On the Emotion Report Form, 16 emotions could be rated: sadness, fear, shame, contentment, guilt, happiness, disgust, despair, positivity, enjoyment, irritation, hope, anger, pride, negativity, anxiety. Ratings were made on a 10-point Likert scale (1 = none, 10 = a great deal). In one case, the participant would not fill in the Emotion Report Form himself, but would read the Emotion Report Form, filled in by the speaker, to be able to learn which emotional values belong to the acoustic (and semantic) features in the speaker’s voice. After filling in the last Emotion Report Form, the participant was thanked for his/her work and rewarded with a chocolate bar.
4.5 Results

**EXPERIMENT 1 & 2**

4.5.1 Human vs. machine performance; answering questions 1, 2 and 3

In this subsection, the following research questions are answered:

1. Are humans better or worse than the machine algorithm in the classification of emotions? (Out of 2 recordings, which one has the highest emotional value?). 
2. Are humans better or worse than the machine algorithm in the regression problem? (Given 2 recordings, estimate the change of each emotional state).
3. Are humans better in detecting changing emotions in negative than positive emotions, like the machine algorithm?

To make a direct comparison between humans and the machine algorithm, the performance of the humans on only “NAC” files is shown in Tables 7 and 8. The a priori hypothesis was that the machine learning algorithm would outperform the humans, because the NAC files contain no semantic cues for the humans and the voices sound a bit ‘monotone’ or ‘emotionless’. The significance of the results presented in table 4.8 are analysed using a one-tailed unpaired t-test based on the a priori hypothesis. The significance of the results presented in Table 7 were analysed with a test, because the performance data is nominal.

Answering question 1: compared to the machine algorithm, humans did not outperform the machine algorithm on any emotion in the classification problem of the “NAC” files. Actually, the machine algorithm outperformed the humans on all emotions, from which the following have significant performance differences: sadness, fear, content, disgust, irritation, anger, pride, anxiety. No significant difference was found for: shame, happiness, positivity, enjoyment, hope and negativity. For guilt and despair trends were found, directing in the way of the machine algorithm performing better in detecting changes in these emotions than humans.

Looking at the regression problem, question 2, in comparison with the machine algorithm, humans performed worse on all emotions. Significant differences were found for almost all emotions, namely: sadness, fear, content, happiness, disgust, despair, positivity, enjoyment, irritation and anxiety. For the other emotions, shame, hope, anger and pride a trend was found. Guilt is the only emotion for which no significant difference was found. These results indicate, that the machine algorithm is better in predicting the size of change in intensity of an emotion, than humans.
Answering question 3: the results do not indicate that humans are better in detecting changes in negative emotions than positive emotions, based on the accuracies.

Note that the results on the “NAC” files only (Tables 4.7 and 7.8) have to be taken with caution, because of the modest number of recording pairs in the experimental setup for humans (only 40 recordings of 20 speakers; 20 pairs), while the training and test sets of the machine algorithm could use a total of 225 recordings of 75 different speakers; 225 pairs.

For the classification problem, two classes were chosen: "increase" or "decrease" of intensity of an emotion. Therefore, for each emotion only pairs of recordings were considered, that had different emotional intensity. For example, for the humans, there were only 11 pairs of recordings with different intensity of "shame"; the remaining 9 pairs had the same intensity of this emotion and were not taken into account, see Table 4.7. To make a better comparison between the machine and the humans, based on the number of recordings, the experiment 2 was performed, in which the number of recording pairs of the humans are comparable to that of the machine algorithm.

Table 4.7. Results of Experiment 1: the humans on the classification problem on only “NAC” files, like the machine algorithm (only 40 recordings of 20 speakers; 20 pairs).

<table>
<thead>
<tr>
<th>Emotion</th>
<th>Human Performance</th>
<th>Machine Performance</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>N</td>
<td>N correct</td>
</tr>
<tr>
<td>sadness</td>
<td>19</td>
<td>7</td>
</tr>
<tr>
<td>fear</td>
<td>19</td>
<td>8</td>
</tr>
<tr>
<td>shame</td>
<td>11</td>
<td>8</td>
</tr>
<tr>
<td>content</td>
<td>20</td>
<td>7</td>
</tr>
<tr>
<td>guilt</td>
<td>10</td>
<td>3</td>
</tr>
<tr>
<td>happiness</td>
<td>20</td>
<td>8</td>
</tr>
<tr>
<td>disgust</td>
<td>18</td>
<td>2</td>
</tr>
<tr>
<td>despair</td>
<td>14</td>
<td>6</td>
</tr>
<tr>
<td>positivity</td>
<td>20</td>
<td>11</td>
</tr>
<tr>
<td>enjoyment</td>
<td>20</td>
<td>9</td>
</tr>
<tr>
<td>irritation</td>
<td>18</td>
<td>5</td>
</tr>
<tr>
<td>hope</td>
<td>18</td>
<td>8</td>
</tr>
<tr>
<td>anger</td>
<td>17</td>
<td>3</td>
</tr>
<tr>
<td>pride</td>
<td>16</td>
<td>8</td>
</tr>
<tr>
<td>negativity</td>
<td>19</td>
<td>9</td>
</tr>
<tr>
<td>anxiety</td>
<td>20</td>
<td>6</td>
</tr>
</tbody>
</table>
Table 4.8. Results of Experiment 1: the humans on the regression problem on only “NAC” files, like the machine algorithm (40 recordings, 20 pairs of 20 different speakers).

<table>
<thead>
<tr>
<th>Emotion</th>
<th>Human Performance</th>
<th>Machine Performance</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Mean</td>
<td>Absolute Difference</td>
</tr>
<tr>
<td>sadness</td>
<td>20</td>
<td>3.95</td>
</tr>
<tr>
<td>fear</td>
<td>20</td>
<td>4.125</td>
</tr>
<tr>
<td>shame</td>
<td>20</td>
<td>1.4</td>
</tr>
<tr>
<td>content</td>
<td>20</td>
<td>4.65</td>
</tr>
<tr>
<td>guilt</td>
<td>20</td>
<td>1.7</td>
</tr>
<tr>
<td>happiness</td>
<td>20</td>
<td>5.15</td>
</tr>
<tr>
<td>disgust</td>
<td>20</td>
<td>5.15</td>
</tr>
<tr>
<td>despair</td>
<td>20</td>
<td>3.2</td>
</tr>
<tr>
<td>positivity</td>
<td>20</td>
<td>4.7</td>
</tr>
<tr>
<td>enjoyment</td>
<td>20</td>
<td>4.65</td>
</tr>
<tr>
<td>irritation</td>
<td>20</td>
<td>3.8</td>
</tr>
<tr>
<td>hope</td>
<td>20</td>
<td>3.15</td>
</tr>
<tr>
<td>anger</td>
<td>20</td>
<td>3.25</td>
</tr>
<tr>
<td>pride</td>
<td>20</td>
<td>2.9</td>
</tr>
<tr>
<td>negativity</td>
<td>20</td>
<td>3.95</td>
</tr>
<tr>
<td>anxiety</td>
<td>20</td>
<td>5.4</td>
</tr>
</tbody>
</table>

Tables 4.9 and 4.10 show the results of human performance on the classification and regression problem in experiment 2. These results are calculated over all type of files that humans listened to. The machine algorithm was only trained and tested on “NAC” files, which seem to give humans a benefit of having semantic cues on top of the acoustic cues, especially in the “CR” and “TAR” files. The a priori hypothesis was that the machine learning algorithm would perform differently than the humans, but because the humans now had an advantage compared to experiment 1 (now they could also use semantic cues), there was no hypothesis formed a priori about who would perform better, the humans or the machine algorithm. The results in table 4.10 were therefore analysed using two-tailed unpaired t-tests. The results in Table 4.9 were analysed with a test, because the data acquired are nominal.

Answering questions 1 and 2: even though the humans had an advantage compared to the machine learning algorithm, the humans performed worse than the machine algorithm on both the classification and regression...
problem. First of all, on the classification problem, compared to the human performance, the machine algorithm detected changes in sadness, fear, shame, content, guilt, disgust, despair, irritation, anger, pride, negativity and anxiety significantly better. For hope a trend was found. No significant differences were found for happiness, positivity and enjoyment. The overall performance of the machine algorithm on the classification problem is therefore better than the human performance: significantly better on 12 out of 16 emotions. When looking at the regression problem, in comparison with the humans performance, the machine algorithm performed significantly better on sadness, shame and anxiety. For content, happiness, irritation and pride trends were found. On all other emotions, the performances did not differ significantly.

Answering question 3: based on the accuracies, there seems to be no clear difference between detecting positive versus negative emotions for humans.

Table 4.9. Results of Experiment 2: the humans on the classification problem on all four types of files (168 recordings of 42 speakers; maximum of 111 pairs for the humans). Error is measured by the ratio of misclassified record (misclassification rate).

<table>
<thead>
<tr>
<th>Emotion</th>
<th>Human Performance</th>
<th>Machine Performance</th>
<th>P*</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>N</td>
<td>N Correct</td>
<td>Accuracy</td>
</tr>
<tr>
<td>sadness</td>
<td>70</td>
<td>27</td>
<td>39%</td>
</tr>
<tr>
<td>fear</td>
<td>70</td>
<td>31</td>
<td>44%</td>
</tr>
<tr>
<td>shame</td>
<td>41</td>
<td>24</td>
<td>59%</td>
</tr>
<tr>
<td>content</td>
<td>78</td>
<td>44</td>
<td>56%</td>
</tr>
<tr>
<td>guilt</td>
<td>34</td>
<td>11</td>
<td>32%</td>
</tr>
<tr>
<td>happiness</td>
<td>78</td>
<td>41</td>
<td>53%</td>
</tr>
<tr>
<td>disgust</td>
<td>72</td>
<td>21</td>
<td>29%</td>
</tr>
<tr>
<td>despair</td>
<td>53</td>
<td>23</td>
<td>43%</td>
</tr>
<tr>
<td>positivity</td>
<td>78</td>
<td>47</td>
<td>60%</td>
</tr>
<tr>
<td>enjoyment</td>
<td>78</td>
<td>48</td>
<td>62%</td>
</tr>
<tr>
<td>irritation</td>
<td>65</td>
<td>22</td>
<td>34%</td>
</tr>
<tr>
<td>hope</td>
<td>71</td>
<td>36</td>
<td>51%</td>
</tr>
<tr>
<td>anger</td>
<td>60</td>
<td>20</td>
<td>33%</td>
</tr>
<tr>
<td>pride</td>
<td>61</td>
<td>23</td>
<td>38%</td>
</tr>
<tr>
<td>negativity</td>
<td>72</td>
<td>33</td>
<td>46%</td>
</tr>
<tr>
<td>anxiety</td>
<td>70</td>
<td>29</td>
<td>41%</td>
</tr>
</tbody>
</table>
Table 4.10. Results of Experiment 2: the humans on the classification problem on all four types of files (168 recordings of 42 speakers; maximum of 111 pairs for the humans).

<table>
<thead>
<tr>
<th>Emotion</th>
<th>N</th>
<th>N_correct</th>
<th>Accuracy</th>
<th>N</th>
<th>N_Correct</th>
<th>Accuracy</th>
<th>p-value</th>
</tr>
</thead>
<tbody>
<tr>
<td>sadness</td>
<td>111</td>
<td>2.6216</td>
<td>2.40</td>
<td>225</td>
<td>2.2103</td>
<td>1.91</td>
<td>0.09</td>
</tr>
<tr>
<td>fear</td>
<td>111</td>
<td>2.8378</td>
<td>2.59</td>
<td>225</td>
<td>2.4451</td>
<td>2.08</td>
<td>0.135</td>
</tr>
<tr>
<td>shame</td>
<td>111</td>
<td>1.4775</td>
<td>1.35</td>
<td>225</td>
<td>1.0665</td>
<td>1.14</td>
<td>0.004</td>
</tr>
<tr>
<td>content</td>
<td>111</td>
<td>3.2162</td>
<td>2.77</td>
<td>225</td>
<td>2.6842</td>
<td>2.11</td>
<td>0.052</td>
</tr>
<tr>
<td>guilt</td>
<td>111</td>
<td>1.3784</td>
<td>1.83</td>
<td>225</td>
<td>1.2671</td>
<td>1.55</td>
<td>0.582</td>
</tr>
<tr>
<td>happiness</td>
<td>111</td>
<td>3.6126</td>
<td>2.82</td>
<td>225</td>
<td>3.0792</td>
<td>2.18</td>
<td>0.057</td>
</tr>
<tr>
<td>disgust</td>
<td>111</td>
<td>3.2523</td>
<td>2.72</td>
<td>225</td>
<td>3.0250</td>
<td>2.31</td>
<td>0.424</td>
</tr>
<tr>
<td>despair</td>
<td>111</td>
<td>2.0721</td>
<td>2.31</td>
<td>225</td>
<td>1.8274</td>
<td>1.85</td>
<td>0.296</td>
</tr>
<tr>
<td>positivity</td>
<td>111</td>
<td>3.3243</td>
<td>2.62</td>
<td>225</td>
<td>3.0492</td>
<td>2.19</td>
<td>0.341</td>
</tr>
<tr>
<td>enjoyment</td>
<td>111</td>
<td>3.1622</td>
<td>2.90</td>
<td>225</td>
<td>3.3414</td>
<td>2.26</td>
<td>0.535</td>
</tr>
<tr>
<td>irritation</td>
<td>111</td>
<td>2.4324</td>
<td>1.98</td>
<td>225</td>
<td>2.0603</td>
<td>1.74</td>
<td>0.08</td>
</tr>
<tr>
<td>hope</td>
<td>111</td>
<td>2.7297</td>
<td>2.39</td>
<td>225</td>
<td>2.4571</td>
<td>1.85</td>
<td>0.251</td>
</tr>
<tr>
<td>anger</td>
<td>111</td>
<td>2.0991</td>
<td>2.19</td>
<td>225</td>
<td>2.3607</td>
<td>2.00</td>
<td>0.291</td>
</tr>
<tr>
<td>pride</td>
<td>111</td>
<td>2.5045</td>
<td>2.12</td>
<td>225</td>
<td>2.1387</td>
<td>1.71</td>
<td>0.09</td>
</tr>
<tr>
<td>negativity</td>
<td>111</td>
<td>3.0721</td>
<td>2.64</td>
<td>225</td>
<td>2.7096</td>
<td>2.07</td>
<td>0.17</td>
</tr>
<tr>
<td>anxiety</td>
<td>111</td>
<td>3.3784</td>
<td>2.99</td>
<td>225</td>
<td>2.7788</td>
<td>2.33</td>
<td>0.045</td>
</tr>
</tbody>
</table>

**EXPERIMENT 3, 4 & 5**

5.5.2 More characteristics of human performance; answering questions 4, 5 and 6

In this subsection, the answers to the following research questions are showed:

(4) Are humans better in predicting changing emotions in their own voice than somebody else’s voice?

(5) Are humans better in detecting changing emotions when they can also use semantic cues in the audio files, besides the acoustic cues?

(6) Are humans better in detecting changing emotions when they learn how the speaker rated his own feelings than when they did not learn this?

Below, in Table 4.11, the results of experiment 3 are shown. The average differences of the ratings of the participants on the speaker’s felt
emotions, based on their recordings are shown. For all types of files, for all emotions except pride, the participants were better in rating the emotional intensities of their own voice than that of others. When only looking at the “NAC” files, on all emotions except disgust and pride, the participants were better in rating the emotional intensities of their own voice than that of others. When only looking at the non-“NAC” files, on all emotions except enjoyment, hope and pride, the participants were better in rating the emotional intensities of their own voice than that of others. When looking at the averages over all emotions, the participants were always better in rating the emotional intensities of their own voice than that of others. These results indicate that it is easier to detect the intensities of emotions in one’s own voice than that of a stranger.

Table 4.11. Results of Experiment 3: average absolute difference in emotional ratings of one’s own voice and of another person’s voice.* = p<.1, ***= p<.05, ****= p<.001

<table>
<thead>
<tr>
<th>Emotion</th>
<th>All type of files</th>
<th>Only “NAC” files</th>
<th>Non-“NAC” files</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Average absolute difference own voice</td>
<td>Average absolute difference other person’s voice</td>
<td>Average absolute difference own voice</td>
</tr>
<tr>
<td>sadness</td>
<td>1.64**</td>
<td>2.52**</td>
<td>1.82</td>
</tr>
<tr>
<td>fear</td>
<td>1.93*</td>
<td>2.56*</td>
<td>2.21</td>
</tr>
<tr>
<td>shame</td>
<td>1.36**</td>
<td>2.02**</td>
<td>1.36</td>
</tr>
<tr>
<td>content</td>
<td>2.32</td>
<td>2.43</td>
<td>2.61</td>
</tr>
<tr>
<td>guilt</td>
<td>1.00***</td>
<td>2.19***</td>
<td>0.96**</td>
</tr>
<tr>
<td>happiness</td>
<td>2.50</td>
<td>2.75</td>
<td>2.61</td>
</tr>
<tr>
<td>disgust</td>
<td>2.63</td>
<td>2.64</td>
<td>3.00</td>
</tr>
<tr>
<td>despair</td>
<td>1.50*</td>
<td>2.14*</td>
<td>1.36</td>
</tr>
<tr>
<td>positivity</td>
<td>2.07*</td>
<td>2.65*</td>
<td>2.07</td>
</tr>
<tr>
<td>enjoyment</td>
<td>2.32</td>
<td>2.60</td>
<td>2.29</td>
</tr>
<tr>
<td>irritation</td>
<td>2.39</td>
<td>2.77</td>
<td>2.39</td>
</tr>
<tr>
<td>hope</td>
<td>2.16</td>
<td>2.20</td>
<td>2.04</td>
</tr>
<tr>
<td>anger</td>
<td>1.70</td>
<td>2.06</td>
<td>2.00</td>
</tr>
<tr>
<td>pride</td>
<td>2.75</td>
<td>2.47</td>
<td>3.07</td>
</tr>
<tr>
<td>negativity</td>
<td>1.93**</td>
<td>2.72**</td>
<td>1.86*</td>
</tr>
<tr>
<td>anxiety</td>
<td>2.20</td>
<td>2.77</td>
<td>2.50</td>
</tr>
<tr>
<td>Average over all emotions</td>
<td>2.02***</td>
<td>2.47***</td>
<td>2.13**</td>
</tr>
</tbody>
</table>

Below, in Table 4.12, the results of experiment 4 are shown. The average differences of the ratings of the participants on the speaker’s felt emotions, based on their recordings are shown. The performances on the “NAC” files
are compared to that of the “MEM”, “TAR” and “CR” files together. Differences could indicate that semantic cues are the reason for a better performance on the non-“NAC” files, since there were no semantic cues in the “NAC” files. The result show that the participants performed better in rating sadness, content, happiness, disgust, positivity, enjoyment, irritation, anger, pride and negativity in the non-“NAC” files conditions, but worse in rating fear, shame, guilt, despair, hope and anxiety.

When looking at the averages over all emotions, the participants were marginally better in rating the emotional intensities of the non-“NAC” files than the “NAC” files. These results do not confirm the expectation that humans can rate the emotional intensity better of recordings that include acoustic and semantic cues, than recordings with acoustic cues alone.

Table 4.12. Results of Experiment 4: average absolute differences in emotional ratings of “NAC” files versus “CR”, “TAR” and “MEM” files together. *=p<.1

<table>
<thead>
<tr>
<th>Emotion</th>
<th>Average absolute difference “NAC” files</th>
<th>Average absolute difference “MEM”+ ”CR”+ ”TAR” files</th>
</tr>
</thead>
<tbody>
<tr>
<td>sadness</td>
<td>2.32</td>
<td>2.07</td>
</tr>
<tr>
<td>fear</td>
<td>2.32</td>
<td>2.33</td>
</tr>
<tr>
<td>shame</td>
<td>1.71</td>
<td>1.85</td>
</tr>
<tr>
<td>content</td>
<td>2.62</td>
<td>2.15</td>
</tr>
<tr>
<td>guilt</td>
<td>1.53</td>
<td>1.99</td>
</tr>
<tr>
<td>happiness</td>
<td>2.87</td>
<td>2.43</td>
</tr>
<tr>
<td>disgust</td>
<td>2.80</td>
<td>2.46</td>
</tr>
<tr>
<td>despair</td>
<td>1.84</td>
<td>1.99</td>
</tr>
<tr>
<td>positivity</td>
<td>2.51</td>
<td>2.36</td>
</tr>
<tr>
<td>enjoyment</td>
<td>2.75</td>
<td>2.23</td>
</tr>
<tr>
<td>Irritation</td>
<td>2.66</td>
<td>2.61</td>
</tr>
<tr>
<td>hope</td>
<td>2.15</td>
<td>2.22</td>
</tr>
<tr>
<td>anger</td>
<td>2.08</td>
<td>1.77</td>
</tr>
<tr>
<td>pride</td>
<td>2.81</td>
<td>2.32</td>
</tr>
<tr>
<td>negativity</td>
<td>2.52</td>
<td>2.34</td>
</tr>
<tr>
<td>anxiety</td>
<td>2.53</td>
<td>2.59</td>
</tr>
<tr>
<td>Average over all emotions*</td>
<td>2.38</td>
<td>2.23</td>
</tr>
</tbody>
</table>

Below, in Table 4.13, the results of experiment 5 are shown. The table contains average differences of the ratings of the participants on the speaker’s felt emotions, based on their recordings. The performances under the ‘learning
condition are compared to the condition without learning. Differences could indicate that learning improves human performance, which was the expected finding. The results show that the participants performed better in rating fear, content, happiness, disgust, enjoyment, irritation, hope, anger, pride and anxiety, but not in rating: sadness, shame, guilt, positivity and negativity. When looking at the averages over all emotions, the participants were marginally better in rating the emotional intensities under the learning condition than under the non-learning condition. These results indicate, that overall, humans can rate the emotional intensity marginally better of recordings when they have seen one of the speaker’s own ratings with one of his recording, than when not.

Table 4.13. Results of Experiment 5: average absolute differences in emotional ratings of the condition with learning versus without learning. *=p<.05, **= p<0.001

<table>
<thead>
<tr>
<th>Emotion</th>
<th>Average absolute difference with learning</th>
<th>Average absolute difference without learning</th>
</tr>
</thead>
<tbody>
<tr>
<td>sadness</td>
<td>2.23</td>
<td>2.17</td>
</tr>
<tr>
<td>fear</td>
<td>2.13</td>
<td>2.38</td>
</tr>
<tr>
<td>shame</td>
<td>1.98</td>
<td>1.71</td>
</tr>
<tr>
<td>content</td>
<td>2.28</td>
<td>2.44</td>
</tr>
<tr>
<td>guilt</td>
<td>1.80</td>
<td>1.71</td>
</tr>
<tr>
<td>happiness</td>
<td>2.60</td>
<td>2.68</td>
</tr>
<tr>
<td>disgust</td>
<td>2.35</td>
<td>2.76</td>
</tr>
<tr>
<td>despair</td>
<td>1.83</td>
<td>1.97</td>
</tr>
<tr>
<td>positivity</td>
<td>2.60</td>
<td>2.37</td>
</tr>
<tr>
<td>enjoyment</td>
<td>2.20</td>
<td>2.57</td>
</tr>
<tr>
<td>irritation</td>
<td>2.55</td>
<td>2.68</td>
</tr>
<tr>
<td>Hope*</td>
<td>1.63</td>
<td>2.37</td>
</tr>
<tr>
<td>anger</td>
<td>1.85</td>
<td>1.99</td>
</tr>
<tr>
<td>Pride**</td>
<td>1.50</td>
<td>2.94</td>
</tr>
<tr>
<td>negativity</td>
<td>2.48</td>
<td>2.40</td>
</tr>
<tr>
<td>anxiety</td>
<td>2.43</td>
<td>2.59</td>
</tr>
<tr>
<td>Average over all emotions*</td>
<td>2.15</td>
<td>2.36</td>
</tr>
</tbody>
</table>

4.6 Visualisation

In this section, the task to reduce the dimensionality of the emotional data (originally 16 dimensions) and to visualise it, is addressed. At the beginning of this chapter, an intelligent agent was envisioned that is built into a
Part II: Modelling Emotion Contagion and Emotion Recognition

phone and who can measure the emotion in the voice of its user. The previous sections addressed a machine algorithm that can endow an intelligent agent with emotion recognition from speech. The next goal is to design a cognitive model for this agent, so that it can visualize multidimensional data collected from its user in 2-d space. How exactly can an intelligent agent, give an objective insight into your emotions? By showing you your own face, as if you are looking into a mirror? That could fail, because we often don’t really see ourselves properly in the mirror. Think of people with an eating disorder that perceive themselves as being overweight in the mirror, while in fact they are underweight. The same can happen with emotions: you could perceive your own expressed emotion stronger or weaker than it really is. Therefore another visualisation technique is necessary. Here, it was chosen to use a dimensionality reduction technique which can map multidimensional data into two dimensions, while preserving as much information as possible.

There are many methods for dimensionality reduction, for example: Principal Component Analysis (PCA), Multidimensional Scaling (MDS), Locally Linear Embedding (LLE) and Self-Organizing Maps (SOM), [14]. For this research PCA analysis was chosen, for several reasons. First, a technique was necessary that does not need a lot of computing power, because it has to work on a smart phone. In contrast to PCA, MDS and LLE would require the whole algorithm to be rerun every single time a new speech unit is analysed. Second, PCA requires no tuning and is fully deterministic. Furthermore, PCA is a well-established standard in psychometrics and provides closed formulas to compute coordinates of data in new dimensions. MDS and LLE are more visualisation techniques; there is no formula that describes the mapping. SOM is also a visualisation technique; it is not an analytical technique that measures the structure in the data.

4.6.1 Dimensional theory of emotion

There are different theories of emotions, amongst others: dimensional models of emotions and the theory of basic emotions, [16], [6]. Dimensional models of emotions assume that emotions are dependent upon each other, whereas, the basic emotions theory assumes that emotions are independent of each other. According to the basic emotions theory, emotions can be labelled as anger, disgust, fear, happiness, sadness and surprise, see [6]. These labels do not give many options for the visualization of emotions. For the purpose of visualizing emotions to the user of our envisioned application, it is more interesting to place emotions within a two or three-dimensional model of affective dimensions. Another reason for choosing the dimensional model of emotions, is that a dimensional model is very suitable for visualizing spontaneous, naturally occurring emotions, because it allows for continuous
description. In dimensional theory, emotions are usually placed within the dimensions valence (from positive to negative) and arousal (from high to low), [16], [20]. In [3] a third dimension called stance (from open to close) was added.

Figure 4.2. Visualisation of the 16 emotions according to the circumplex model of emotions in [16] and [20]

In Figure 4.2, the 16 emotions that the intelligent agent can detect in speech are visualized according to the circumplex model of emotion, [16], [20]. In this figure, the labels "anger", "anxiety", "irritation", "guilt", "happiness" and "content" correspond to the states "angry", "alarmed", "annoyed", "guilty", "happy", and "content" as described in [16], respectively, while "fear", "negativity", "sadness" and "positivity" correspond to respective states described in [20]. The emotions outside the circle, shame, disgust, despair, enjoyment, pride and hope were not modelled in [16] or [20] and were left outside the circle. The valence of these emotions is known: shame, disgust and despair are negative emotions and enjoyment, pride and hope are positive emotions. The arousal is not clear beforehand according to the circumplex models. It will be interesting if the emotions in the current and original experiment correspond with the dimensional modelling of the circumplex
model. If they differ, it can be seen how the ratings of people listening to a voice differ from the ratings of the speakers about their internal feelings.

![Figure 4.3. First two principal components of all emotion vectors of original experiment](image)

4.6.2 PCA analysis of research data

PCA Analysis has been performed on all emotion vectors of the 111 participants of the original experiment from which the emotion vectors and recordings of 75 participants (in the experimental conditions) were used in the current experiments. Each participant rated his/her emotions 3 times during the original experiment and all three emotion vectors for each participant were used in the PCA analysis. Also PCA Analysis has been performed on the judged emotion vectors of the current experiment 1. PCA finds a linear combination, so that multiple principal components can explain the data together for a maximum of 100%. A number of transformations were made. First, the range of scores from [1-10] was transformed to [0-9] just by subtracting 1 from each score. Second, every vector of 16 scores was divided by their sum, so that every vector would sum up to 1:

\[ s_i = \frac{s_i}{s_1 + s_2 + \ldots + s_{16}}, \text{ for } i = 1, \ldots, 16. \]

The motivation for this
normalisation is that it corrects for the response bias people have. Some people tend to score at the ends of the Likert scale, some people tend to score around the middle of the Likert Scale. To correct for this, everybody can now score within the same interval [0,1]. Third, each emotion was standardised: calculate for each emotion e its mean value mean(e) and standard deviation std(e) and apply the formula: zscore(s)=(s-mean(e))/std(e), where s is a score of e given by a user. After the transformations, the principal components were calculated.

Table 4.14. Factor loadings of the first three principal components, belonging to Figure 4.3.

<table>
<thead>
<tr>
<th>Emotions</th>
<th>Factor loading C1</th>
<th>Factor loading C2</th>
<th>Factor loading C3</th>
</tr>
</thead>
<tbody>
<tr>
<td>negativity</td>
<td>-0.29</td>
<td>-0.10</td>
<td>0.09</td>
</tr>
<tr>
<td>anger</td>
<td>-0.28</td>
<td>0.05</td>
<td>0.16</td>
</tr>
<tr>
<td>disgust</td>
<td>-0.27</td>
<td>-0.17</td>
<td>0.01</td>
</tr>
<tr>
<td>anxiety</td>
<td>-0.26</td>
<td>-0.28</td>
<td>-0.39</td>
</tr>
<tr>
<td>fear</td>
<td>-0.25</td>
<td>-0.25</td>
<td>-0.38</td>
</tr>
<tr>
<td>despair</td>
<td>-0.24</td>
<td>0.13</td>
<td>-0.15</td>
</tr>
<tr>
<td>sadness</td>
<td>-0.22</td>
<td>0.01</td>
<td>0.03</td>
</tr>
<tr>
<td>irritation</td>
<td>-0.18</td>
<td>0.02</td>
<td>0.57</td>
</tr>
<tr>
<td>shame</td>
<td>-0.17</td>
<td>0.37</td>
<td>0.31</td>
</tr>
<tr>
<td>guilt</td>
<td>-0.13</td>
<td>0.52</td>
<td>-0.03</td>
</tr>
<tr>
<td>pride</td>
<td>0.18</td>
<td>0.43</td>
<td>-0.36</td>
</tr>
<tr>
<td>hope</td>
<td>0.19</td>
<td>0.35</td>
<td>-0.23</td>
</tr>
<tr>
<td>enjoyment</td>
<td>0.30</td>
<td>-0.07</td>
<td>-0.00</td>
</tr>
<tr>
<td>content</td>
<td>0.30</td>
<td>-0.17</td>
<td>0.11</td>
</tr>
<tr>
<td>positivity</td>
<td>0.31</td>
<td>-0.20</td>
<td>0.12</td>
</tr>
<tr>
<td>happiness</td>
<td>0.32</td>
<td>-0.12</td>
<td>0.12</td>
</tr>
<tr>
<td>Explained variance</td>
<td>C1=0.49149</td>
<td>C1+C2=0.58229</td>
<td>C1+C2+C3=0.65053</td>
</tr>
</tbody>
</table>

The results of the first PCA analysis are shown in Figure 4.3 and Table 4.14. Figure 4.3 shows that the first principal component corresponds with the valence dimension of the circumplex dimensional model of emotions; all negative emotions are on the left and all positive emotions are on the right. The second principal component seems to correspond with the energy dimension of the circumplex model for the emotions, but then upside down. It could make sense if fear, anxiety and disgust are the more active emotions and guilt and shame more passive (more internal feelings). The same holds for the positive emotions: pride and hope could be the more passive emotions (more internal feelings) and enjoyment, happiness, content and positivity the more active emotions.
Figure 4.4. First two principal components of all emotion vectors of speakers in experiment 1 (subset of the emotion vectors in Figure 4.3), but then scored by others: the 14 participants of experiment 1

The second PCA analysis was performed in the same way for the ratings of the participants in Experiment 1. Figure 4.4 and Table 4.15 show the results. It can be seen that when one rates another person different results appear than when the persons rate themselves. Also in Figure 4.4, the first principal component corresponds to the valence dimension of the circumplex model: all negative emotions are on the left and all positive emotions are on the left. It can also be seen that it was hard to differentiate in the intensities between the negative emotions: all negative emotions, besides sadness and negativity, seem to lie close to each other. For positive emotions there is a clearer division in emotions: content, happiness and positivity were rated different than hope, enjoyment and pride. Also positive emotions were rated the opposite of the speakers own ratings. Again, it seems that the second principal component corresponds modestly with the energy dimension of the circumplex model, but then upside down. The most important conclusions are that the speakers’ own ratings of their own feelings corresponds best to the circumplex model of emotions, which in a way validates the felt emotions of
the speakers and this technique to visualize them in the envisioned application. Second, it has been also validated that another person’s rating of your emotion can be very different than how you would rate your own feeling. Therefore, it is not a good idea to let your feelings be judged by other people, but to be judged by the intelligent agent that can learn your feelings, from your own feedback.

Table 4.15. Factor loadings of the first three principal components, belonging to Figure 4.

<table>
<thead>
<tr>
<th>Emotions</th>
<th>Factor loading C1</th>
<th>Factor loading C2</th>
<th>Factor loading C3</th>
</tr>
</thead>
<tbody>
<tr>
<td>despair</td>
<td>-0.27</td>
<td>-0.11</td>
<td>0.08</td>
</tr>
<tr>
<td>anxiety</td>
<td>-0.25</td>
<td>-0.16</td>
<td>-0.42</td>
</tr>
<tr>
<td>fear</td>
<td>-0.25</td>
<td>-0.13</td>
<td>-0.33</td>
</tr>
<tr>
<td>disgust</td>
<td>-0.25</td>
<td>-0.13</td>
<td>-0.29</td>
</tr>
<tr>
<td>anger</td>
<td>-0.23</td>
<td>-0.26</td>
<td>-0.14</td>
</tr>
<tr>
<td>irritation</td>
<td>-0.23</td>
<td>-0.21</td>
<td>0.25</td>
</tr>
<tr>
<td>shame</td>
<td>-0.22</td>
<td>-0.07</td>
<td>0.53</td>
</tr>
<tr>
<td>negativity</td>
<td>-0.19</td>
<td>0.52</td>
<td>0.08</td>
</tr>
<tr>
<td>guilt</td>
<td>-0.18</td>
<td>-0.22</td>
<td>0.42</td>
</tr>
<tr>
<td>sadness</td>
<td>-0.17</td>
<td>0.56</td>
<td>-0.18</td>
</tr>
<tr>
<td>pride</td>
<td>0.21</td>
<td>-0.30</td>
<td>-0.20</td>
</tr>
<tr>
<td>hope</td>
<td>0.29</td>
<td>-0.16</td>
<td>-0.04</td>
</tr>
<tr>
<td>happiness</td>
<td>0.29</td>
<td>0.06</td>
<td>-0.03</td>
</tr>
<tr>
<td>content</td>
<td>0.30</td>
<td>0.13</td>
<td>0.04</td>
</tr>
<tr>
<td>enjoyment</td>
<td>0.30</td>
<td>-0.21</td>
<td>-0.00</td>
</tr>
<tr>
<td>positivity</td>
<td>0.32</td>
<td>0.02</td>
<td>0.04</td>
</tr>
<tr>
<td>Explained variance</td>
<td>C1=0.46868</td>
<td>C1+C2=0.59101</td>
<td>C1+C2+C3=0.6812</td>
</tr>
</tbody>
</table>

4.7 Conclusion

In this research, the goal was to develop a system that will automatically measure changes in the emotional state of a speaker, by analyzing his/her voice. Natural human speech was collected in a laboratory study, from microphones and manually splitted and labelled into meaningful pieces. In total, 207 speech features were extracted. The Random Forests algorithm was used to address a classification problem (out of 2 recordings, which one has the highest emotional value?) and a regression problem (given 2 recordings, estimate the change of each emotional state).

Results showed that predicting the direction of change of emotions can be done about 7% better than the baseline (the most frequent class label), while predicting the change of intensity, measured by the Mean Squared Error, can be done about 9.7% better than the baseline (the mean value of change).
Moreover, it turned out that changes of intensity in negative emotions are more predictable than changes in positive emotions: the relative error reduction rate for these two groups was 11.2% and 7.1%, respectively. At first sight, these error reductions could seem relatively small, but in fact they are not. Given the modest size of the training set (only 3 recordings per person), these improvements are quite remarkable, together with the fact that the performance is significantly better than a random guess. Moreover, in the field of affective sensing these improvements are quite substantial, for example see significant error reduction rates of only 7% in [21].

In general, it is much easier to detect changes in negative emotions than in positive ones. This is beneficiary for the envisioned application, where an intelligent agent needs to detect negative mood, like anger, despair, fear and anxiety, to prevent the user from depression or to council the user into a positive mood. Occurrence of emotions like fear, shame, and despair can be predicted, on average, 29.2% better than the baseline; change in their intensity can be predicted about 12.9% better than the baseline. Some emotions are very difficult to predict. For example, guilt, happiness, hope, and pride seem to be not predictable at all (see Table 4.2).

The validation experiment investigated how human performance compared to the machine performance in 5 experiments. Experiment 1 and 2 investigated the following research questions: (1) Are humans better or worse than the machine algorithm in the classification of emotions? (out of 2 recordings, which one has the highest emotional value?), (2) Are humans better or worse than the machine algorithm in the regression problem? (Given 2 recordings, estimate the change of each emotional state), (3) Are humans better in detecting changing emotions in negative than positive emotions, like the machine algorithm.

The answer to the first research question is that the machine algorithm significantly outperformed the humans in experiment 1 on 8 out of 16 emotions and in experiment 2 on 12 out of 16 emotions. Happiness was the only emotion in both experiments, for which there was no significant difference found. This indicates, that overall, the machine algorithm is better in detecting changes in emotions than humans.

For question 2, results do not clearly indicate that the machine algorithm is better in predicting the size of change in intensity of emotions than humans. In experiment 1, the machine algorithm did perform significantly better on 10 out of 16 emotions. For 5 more emotions a trend was found. In experiment 2 though, the machine algorithm outperformed the humans significantly on only 3 emotions, from which the performance on sadness and anxiety correspond with that of experiment 1, and a trend was found for 4 more emotions. Experiments 1 and 2 together, indicate that the machine
algorithm is at least better in predicting the size of the change in anxiety and sadness, but for the other emotions more experiments need to be conducted to make clear interpretations.

For question 3, no clear indications were found that the humans perform better in detecting changes in negative than positive emotions, like the machine algorithm.

Experiments 3 to 5 investigated the following research questions: (4) Are humans better in predicting changing emotions in their own voice than somebody else’s voice?, (5) Are humans better in detecting changing emotions when they can also use semantic cues in the audio files, besides the acoustic cues?, (6) Are humans better in detecting changing emotions when they learn how the speaker rated his own feelings than when they did not learn this?

Results showed that over all emotions, the participants were always better in rating the emotional intensities of their own voice than that of others. These results indicate that it is easier to detect the intensities of emotions in one’s own voice than that of a stranger.

Results of experiment 4 do not confirm the expectation that humans can rate the emotional intensity better of recordings that include acoustic and semantic cues, than recordings with acoustic cues alone. The result show that the participants performed better in rating sadness, content, happiness, disgust, positivity, enjoyment, irritation, anger, pride and negativity in the non-“NAC files conditions, but worse in rating fear, shame, guilt, despair, hope and anxiety. When looking at the averages over all emotions, the participants were marginally better in rating the emotional intensities of the non-“NAC” files than the “NAC” files.

Finally, the results of experiment 5 demonstrate that overall emotions, humans can rate the emotional intensity marginally better of recordings when they have seen one of the speaker’s own ratings with one of his recording, than when not. In sum, all the results of the experiments validate that the machine algorithm performs better than humans, which is beneficiary for the envisioned application, where natural non-acted speech has to be processed by the intelligent agent.

In Section 4.5 all emotions were visualised by PCA analysis. The most important findings here, were that the speakers’ own ratings of their own feelings corresponds best to the circumplex model of emotions, which validates the felt emotions of the speakers and this technique to visualize them in the envisioned application. Second, it has been also validated, that another person’s rating of your emotion can be very different than how you would rate your own feeling. Therefore, it is not a good idea to let your feelings be judged by other people, but to be judged by the intelligent agent that can learn your feelings, by your own feedback.
4.8 Discussion
The biggest challenge in our research was a very scarce set of recordings: just 3 records per subject. We believe that with the increase of the size of available data the accuracy of our models would dramatically improve. In practice, this should be easy to achieve: potential users of the final system will have to "tune" it to their specific voice and emotional states by providing numerous speech samples with labels, in the training phase.

Possible applications for the classification and regression algorithm were listed already in the introduction. Other applications are a warning system, a voice-based monitor of physiological functions and a computer game feedback monitor. For example, when a person is angry, aggressive or just furious, the smartphone could generate alerts or warnings like: “you are too excited to drive a car, operate heavy machinery or talk to your children” or “your blood pressure is probably too high right now". We hypothesise that these kind of warnings make the biggest impact if they are composed by the user itself.

Concerning the voice-based monitor of physiological functions; we expect that there is a direct relation between voice characteristics and physiological states of a person, like breath rate, blood pressure, heart rate, sugar level and cholesterol level. We would like to experimentally verify and quantify this assumption, so we could build a very cheap monitoring device which would translate observed characteristic of speech into values of physiological parameters. Finally, the computer game monitoring system could use the learning algorithm to acquire information about the emotional state of the player via his/her voice to either verify if the intended effect of the current game level/environment is really there in the player, or to adjust the game level/environment to the current emotional state of the player.

The current research stems from the vision of an application, where speech is captured, while the person is communicating through a phone, to detect the current mood of a person. Most smart phones offer the possibility to capture the facial expression as well, via the video camera. If this could be incorporated in the envisioned application, multimodal emotion recognition, through speech and facial expression, would be possible. Processing videos requires a lot of computing power though. Therefore, on the short term, real-time multimodal processing seems only feasible by applying facial recognition techniques to detect emotions in photos/still images taken of the user.

Moreover, in a follow up study, more audio files of the same speaker will be acquired, for better accuracy of the system. Besides the speaker's self evaluation of his or her emotional state, it would be interesting to supplement the self-evaluation with a psychophysical measurement, like the Galvanic Skin Response. Finally, trying Support Vector Machines as an alternative modelling method is also part of future work.
References


Part III: Integrated Modelling of Social Contagion and Internal Dynamics

Abstract. In Part III, agent-based models that integrate social contagion and internal dynamics are explored. In Chapter 5, multiple agent models are proposed that either model the contagion of a single type of individual state (an emotion, intention or belief), or that can model the contagion of multiple individual states at the same time, that also interact with each other, internally or socially. The interactions between emotions, intentions and beliefs during collective decision making in an emergency evacuation were modelled and evaluated by automatic property checking and mathematical analysis. Chapter 6 builds on this work, by extending the agents with actions. The model ASCRIBE is proposed: an Agent-based model of Social Contagion Regarding Intentions Beliefs and Emotions. ASCRIBE was tuned to simulate a real-life incident, where a 20,000 people crowd suddenly ran away in panic and 63 people got injured. Statistical validation and comparisons with the empirical data showed that ASCRIBE reproduces the incident better, when contagion of belief, emotion and intention states are included, than when not. Also, in certain circumstances it performs better than another well-known agent model from the literature: the Helbing model. In Chapter 7, ASCRIBE was tuned to simulate the contagion of intentions and beliefs during another real-life situation: the 7-7 London Bombings. Survivor transcripts were formalised into empirical traces and were compared to the simulation traces of the agent model. Formal comparisons showed that the model closely reproduced the real world scenarios.
Chapter 5 - Agent-Based Modelling of the Emergence of Collective States Based on Contagion of Individual States in Groups

Mark Hoogendoorn, Jan Treur, C. Natalie van der Wal, Arlette van Wissen

Abstract. This chapter introduces a neurologically inspired computational model for the dynamics and diffusion of agent states within groups. The model combines an individual model based on Damasio’s Somatic Marker Hypothesis with mutual effects of group members on each other via mirroring of individual states such as emotions, beliefs and intentions. The obtained model shows how this combination of assumed neural mechanisms can form an adequate basis for the emergence of common group beliefs and intentions, while, in addition there is a positive feeling with these common states amongst the group members. A particular issue addressed is how certain types of states may affect other types of states, for example, emotions have an effect on beliefs and intentions, and beliefs may effect emotions.


5.1 Introduction
To express the impossibility of a task, sometimes the expression ‘like managing a herd of cats’ is used, for example, in relation to managing a group of researchers. This is meant to indicate that no single direction or decision will come out of such a group, no matter how hard it is tried. As an alternative, sometimes a reference is made to ‘riding a garden-cart with frogs’. It seems that such a lack of coherence-directed tendency in a group is considered as something exceptional, a kind of surprising, and in a way unfair. However, as each group member is an autonomous agent with his or her own neurological structures, patterns and states, carrying for example, their own emotions, desires, preferences, and intentions, it would be more reasonable to expect that the surprise concerns the opposite side: how is it possible that so often, groups – even those of researchers – develop coherent directions and decisions, and, moreover, why do the group members in some miraculous manner even seem to feel good with these?

Models of social diffusion focus on the process of change within groups. Examples of social diffusion models found in the area of social sciences are: the diffusion of innovations (see e.g. [35]), social movements such as political interests and parties (see e.g. [22]), and crowd behavior, as for instance seen in emergency evacuation (see e.g. [28]). Diffusion models have also been developed in the domain of multi-agent systems in order to study and simulate the behavior of groups of agents. Hereby, models for the spread of information as well as models for the spread of emotions in agent groups have been expressed (see e.g. [36] and [4], [5], [16], respectively).

In this chapter, inspired by the notion of mirroring from the neurological literature (e.g., [14], [23], [24], [31], [32], [33], [30]), first a generic agent-based model is presented for contagion of individual states $S$ such as emotions, beliefs or intentions. The model is a generalization of work on emotion contagion as reported in [4] and [5]. It handles contagion of any individual state $S$, and takes into account personal characteristics for openness and expressivity for state $S$, for positive or negative biases for $S$, and for the extent of amplification for $S$. Moreover parameters are used for the interaction channels between pairs of agents. The generic model has been used for two more complex models each involving multiple types of internal state $S$, and involving specific forms of interaction between different types of states. These more complex models are also presented in the chapter.

One of these two more complex models is a neurologically inspired computational modelling approach for the emergence of group decisions. It incorporates the ideas of somatic marking as a basis for individual decision making, see [2], [10], [12], [13] and mirroring of both emotions and intentions as a basis for mutual influences between group members, see [14], [23], [24],
The model shows how for many cases indeed, the combination of these two neural mechanisms, via the interaction between emotions and intentions, is sufficient to obtain the emergence of common group decisions on the one hand, and, on the other hand, to achieve that the group members have a positive feeling about these decisions.

The other more complex model presented formalizes and simulates the spread of different types of emotions and beliefs in a group. In the literature, results have been reported that indicate that the emotional state of a person influences the information processing ability (see e.g. [3], [26]). Hence, the emotions that are spread in a group and experienced by the individuals can influence how beliefs are spread. So, two interactions are considered: the influence of emotions upon spreading of beliefs, and the occurrence of emotions based on the beliefs. In order to exemplify the approach, extensive simulation runs have been performed in an evacuation domain with scenarios that include varying characteristics of the agents. The model is based on Frederickson’s broaden-and-build theory [17], which states that positive emotions broaden people’s mind-sets: the scopes of attention, cognition, action and the array of percepts, thoughts, and actions presently in mind are widened. The complementary narrowing hypothesis predicts the reverse pattern: negative emotions shrink people’s thought-action repertoires. Support for the broaden and narrowing hypotheses can be found in [18].

The model presented here captures these dynamics between information and emotion. To illustrate, a message containing information about the location and spread of a fire can be expected to elicit fear. Feelings of fear will reinforce the focus of a person towards information relevant to the threat. Furthermore, numerous research studies have shown that information is able to affect emotions. For example, in many psychological experiments fear is elicited by imagery or text to study the process of fear itself or the internal or external signs of fear in humans, see [29]. Another area in psychological research studies fear appeal (persuasive messages that arouse fear) in which it is investigated if fear appeals can motivate behavior change across a variety of behaviors. See for example [37]. In [7] it is argued that the media can influence the perception of fear, via the type of information they spread. Moreover, studies of nonverbal behavior have showed results that emotions can be spread through nonverbal behavior [19]. One can conclude form these many viewpoints and disciplines that emotions, such as fear, can be spread through (non)verbal and textual communications and imagery.

The chapter is organised as follows. In Section 5.2 a brief introduction of the neurological ideas underlying the approach is presented: mirroring and somatic marking. Next, in Section 5.3 the generic agent-based model is described in detail. Section 5.4 presents the more complex model for decision
making in groups based on an interaction between emotions and intentions. In Section 5.5 a number of simulation results are shown and Section 5.6 addresses verification of the model against formally specified properties describing expected emerging patterns. In Section 5.7 the more complex model for the interplay between emotion and belief is introduced formally. Section 5.8 discusses extensive simulation results for this model. In Section 5.9 a mathematical analysis of the models is discussed. The chapter is concluded with a discussion in Section 5.10.

5.2 Some Underlying Neurological Principles

For social interaction, recent neurological findings on the mirroring function of certain neurons have turned out to play an important role (e.g., [14], [23], [24], [31], [32], [33], [34], [30]). Mirror neurons are neurons which, in the context of the neural circuits in which they are embedded, show both a function to prepare for certain actions or bodily changes and a function to mirror states of other persons. They are active not only when a person intends to perform a specific action or body change, but also when the person observes somebody else intending or performing this action or body change. This includes expressing emotions in body states, such as facial expressions. For example, there is strong evidence that (already from an age of just 1 hour) sensing somebody else’s face expression leads (within about 300 milliseconds) to preparing for and showing the same face expression ([21], p. 129-130). The idea is that these neurons and the neural circuits in which they are embedded play an important role in social functioning and in (empathic) understanding of others; (e.g., [14], [23], [34], [30]). The discovery of mirror neurons is often considered a crucial step for the further development of the discipline of social cognition, comparable to the role the discovery of DNA has played for biology, as it provides a biological basis for many social phenomena; cf. [23]. Indeed, when states of other persons are mirrored by some of the person’s own states that at the same time are connected via neural circuits to states that are crucial for the own feelings and actions, then this provides an effective basic mechanism for how in a social context persons fundamentally affect each other’s actions and feelings.

Given the general principles described above, the mirroring function can take place for different types of individual states. In the first place, via body and face expressions, mirroring of emotional states takes place. This type of mirroring occurs in both more complex models presented below in Section 5.4 and Section 5.7. A second way in which a mirroring function can occur is by mirroring of intentions or action tendencies of individuals for the respective decision options. This may work when by verbal and/or nonverbal behaviour,
individuals show in how far they tend to choose for a certain option. For example, in ([20], p.70) action tendencies are described as ‘states of readiness to execute a given kind of action, [which] is defined by its end result aimed at or achieved’. This form of mirroring takes place in the model presented in Section 5.4. A third type of state for which mirroring can take place is for beliefs. Here verbal communication also may occur, but within a group the nonverbal responses may play an even more important role. This type of mirroring takes place in the model presented in Section 5.7.

Cognitive states of a person, such as sensory or other representations often induce emotions felt within this person, as described by neurologist Damasio, [11], [12]; for example:

‘Even when we somewhat misuse the notion of feeling – as in “I feel I am right about this” or “I feel I cannot agree with you” – we are referring, at least vaguely, to the feeling that accompanies the idea of believing a certain fact or endorsing a certain view. This is because believing and endorsing cause a certain emotion to happen.’ ([12], p. 93)

Damasio’s Somatic Marker Hypothesis; cf. [2], [10], [12], [13], is a theory on decision making which provides a central role to emotions felt. Within a given context, each represented decision option induces (via an emotional response) a feeling which is used to mark the option. For example, a strongly negative somatic marker linked to a particular option occurs as a strongly negative feeling for that option. Similarly, a positive somatic marker occurs as a positive feeling for that option. Damasio describes the use of somatic markers in the following way:

‘The somatic marker (...) forces attention on the negative outcome to which a given action may lead, and functions as an automated alarm signal which says: beware of danger ahead if you choose the option which leads to this outcome. The signal may lead you to reject, immediately, the negative course of action and thus make you choose among other alternatives. (...) When a positive somatic marker is juxtaposed instead, it becomes a beacon of incentive.’ ([10], pp. 173-174).

Usually the Somatic Marker Hypothesis is applied to provide endorsements or valuations for options for a person’s actions, thus shaping a decision process. Somatic markers may be innate, but may also be adaptive, related to experiences:

‘Somatic markers are thus acquired through experience, under the control of an internal preference system and under the influence of an external set of circumstances which include not only entities and events with which the organism must interact, but also social conventions and ethical rules. ([10], p. 179).

In the computational model introduced in Section 5.4 somatic marking plays an important role in the spread of intentions in a group. In this model
both emotion and intention mirroring effects are incorporated. Mirroring of emotions indicates how emotions felt in different individuals about a certain considered decision option mutually affect each other, and, assuming a context of somatic marking, in this way affect how by individuals decision options are evaluated in relation to how they feel about them.

In the model introduced in Section 5.7 mirroring of emotions and beliefs is addressed. Here another type of interaction between mirroring of two different types of states is addressed. In one direction, for example, emotions may affect the openness and biases of a person. In the other direction the beliefs affect emotions.

5.3 A Generic Agent-Based Model for Social Diffusion of Individual States

This section introduces the basic agent-based social diffusion model used as a point of departure for this research. This model is a generalization of two existing agent-based emotion contagion models: the absorption model and amplification model (cf. [4], [5]). The model formalizes different aspects and types of social diffusion of mental states, such as absorption, amplification, expressiveness and openness for cognitive and affective (e.g., information and emotion) states, which are inspired by theories on contagion mechanisms. For instance, in [1] Barsade describes an informal model of emotion contagion in which the valence (positive or negative) of the emotion and the energy level with which the emotion is expressed characterize the diffusion.

The basic building block of the model is the definition of the contagion strength between individuals within a group. This contagion strength between agents $B$ and $A$ for any particular state $S$ is defined as follows:

$$
\gamma_{SBA} = \varepsilon_{SB} \cdot \alpha_{SBA} \cdot \delta_{SA}.
$$

(1)

Here $\varepsilon_{SB}$ is the personal characteristic expressiveness of the sender (agent $B$) for $S$, $\delta_{SA}$ the personal characteristic openness of the receiver (agent $A$) for $S$, and $\alpha_{SBA}$ the interaction characteristic channel strength for $S$ from sender $B$ to receiver $A$.

To calculate the level $q_{S,A}$ of an agent $A$ for a specific state $S$ the following calculations are performed. First, the overall contagion strength $\gamma_{S,A}$ from the group towards agent $A$ is calculated:

$$
\gamma_{S,A} = \sum_{B \neq A} \gamma_{SBA}
$$

(2)

This value is used to determine the weighed impact $q_{S,A}^*$ of all the other agents upon state $S$ of agent $A$:

$$
q_{S,A}^* = \sum_{B \neq A} \gamma_{SBA} \cdot q_{SB} / \gamma_{S,A}
$$

(3)
Part III: Integrated Modelling of Social Contagion and Internal Dynamics

How much this external influence actually changes state $S$ of the agent $A$ is determined by two additional personal characteristics of the agent, namely the tendency $\eta_{SA}$ to absorb or to amplify the level of a state and the bias $\beta_{SA}$ towards positive or negative impact for the value of the state. The model to update the value of $q_{SA}(t)$ over time is then expressed as a combination of the absorption and amplification models. The result is a more general model of contagion for any state $S$:

$$q_{SA}(t + \Delta t) = q_{SA}(t) + \gamma_{SA} \cdot \left[ \eta_{SA} \cdot \left( 1 - \beta_{SA} \cdot (1 - q_{SA}(t)) \cdot (1 - q_{SA}(t)) \right) + (1 - \eta_{SA}) \cdot q_{SA}(t) \right] \Delta t$$

(4)

The new value of the state is calculated from the old value, plus the change of the value based upon the contagion. This change is defined as the multiplication of the contagion strength times a factor for the amplification of information plus a factor for the absorption of information. The absorption factor (after $1 - \eta_{SA}(t)$) simply takes the difference between the incoming contagion and the current level. The amplification factor (part of the equation multiplied by $\eta_{SA}(t)$) depends on the tendency of the agent towards more positive (part of equation multiplied by $\beta_{SA}(t)$) or negative (part of equation multiplied by $(1 - \beta_{SA}(t))$) information. Table 5.1 summarizes the most important parameters and states within the model.

Table 5.1 Parameters and states

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>$q_{SA}$</td>
<td>level for state $S$ for agent $A$</td>
</tr>
<tr>
<td>$\varepsilon_{SA}$</td>
<td>extent to which agent $A$ expresses state $S$</td>
</tr>
<tr>
<td>$\delta_{SA}$</td>
<td>extent to which agent $A$ is open to state $S$</td>
</tr>
<tr>
<td>$\eta_{SA}$</td>
<td>tendency of agent $A$ to absorb or amplify state $S$</td>
</tr>
<tr>
<td>$\beta_{SA}$</td>
<td>positive or negative bias of agent $A$ on state $S$</td>
</tr>
<tr>
<td>$\alpha_{SB,A}$</td>
<td>channel strength for state $S$ from sender $B$ to receiver $A$</td>
</tr>
<tr>
<td>$\gamma_{SB,A}$</td>
<td>contagion strength for $S$ from sender $B$ to receiver $A$</td>
</tr>
</tbody>
</table>

5.4 Modelling the Dynamics of Intentions and Emotions in Groups

In this section, based on the neurological principles of somatic marking and mirroring discussed in the previous section, the computational model for group decision making is introduced. To design such a model a choice has to be made for the grain-size: for example, it has to be decided in which level of detail the internal neurological processes of individuals are described. Such a choice depends on the aim of the model. In this case the aim was more to be
able to simulate emerging patterns in groups of individuals, than to obtain a more detailed account of the intermediate neurological patterns and states involved. Therefore the choice was made to abstract to a certain extent from the latter types of intermediate processes. For example, the process of mirroring is described in an abstract manner by a direct causal relation from the emotional state shown by an individual to the emotional state shown by another individual, and the process of somatic marking is described by a direct causal relation for any individual from the emotional state for a certain option to the intention for this option (see Fig. 5.1). The model can easily be refined into a model that also incorporates more detailed intermediate internal processes, for example, based on recursive as-if body loops involving preparation and sensory neuron activations and the states of feeling the emotion, for example, as shown in [25].

![Fig. 5.1. Abstract causal relations induced by mirroring and somatic marking by person A](image)

The abstract model for mirroring described above applies to both emotion and intention states \( S \) or an option \( O \), but does not describe any interplay between them yet. Taking the Somatic Marker Hypothesis on decision making as a point of departure, not only intentions of others, but also one’s own emotions affect one’s own intentions. To incorporate such an interaction, the basic model is extended as follows: to update \( q_{S,A}(t) \) for an intention state \( S \) relating to an option \( O \), both the intention states of others for \( O \) and the \( q_{S',A}(t) \) values for the emotion state \( S' \) for \( O \) are taken into account. These intention and emotion states \( S \) and \( S' \) for option \( O \) are denoted by \( OI \) and \( OE \), respectively:

- Level of emotion for option \( O \) of person \( A \): \( q_{OEA}(t) \)
- Level of intention indication for \( O \) of person \( A \): \( q_{OIA}(t) \)
The combination of the own (positive) emotion level and the rest of the group’s aggregated intention is made by a weighted average of the two:

\[
q_{OIA}^{**}(t) = \left( \frac{\omega_{OIA}}{\omega_{OA}} \right) q_{OIA}^{*}(t) + \left( \frac{\omega_{OEA}}{\omega_{OA}} \right) q_{OEA}(t)
\]

\[\gamma_{OIA}^{*} = \omega \gamma_{OIA}\]

where \(\omega_{OIA}\) and \(\omega_{OEA}\) are the weights for the contributions of the group intention impact (by mirroring) and the own emotion impact (by somatic marking) on the intention of \(A\) for \(O\), respectively, and \(\omega_{OA} = \omega_{OIA} + \omega_{OEA}\). Then the model for the intention and emotion contagion based on mirroring and somatic marking becomes:

\[
q_{OEA}(t + \Delta t) = q_{OEA}(t) + \gamma_{OEA} [\eta_{OEA} (\beta_{OEA} (1 - (1-q_{OEA}^{*}(t))(1-q_{OEA}(t))) + (1 - \beta_{OEA}) q_{OEA}^{*}(t) - q_{OEA}(t)) + (1 - \eta_{OEA}) q_{OEA}^{*}(t) - q_{OEA}(t)] \cdot \Delta t
\]

\[q_{OIA}(t + \Delta t) = q_{OIA}(t) + \gamma_{OIA} [\eta_{OIA} (\beta_{OIA} (1 - (1-q_{OIA}^{**}(t))(1-q_{OIA}(t))) + (1 - \beta_{OIA}) q_{OIA}^{**}(t) - q_{OIA}(t)) + (1 - \eta_{OIA}) q_{OIA}^{**}(t) - q_{OIA}(t)] \cdot \Delta t
\]

5.5 Simulation Results: Interaction Between Intentions and Emotions

The model has been studied in several scenarios in order to examine whether the proposed approach indeed exhibits the patterns that can be expected from literature. The investigated domain consists of a group of four agents who have to make a choice between four different options: A, B, C or D. The model has been implemented in Matlab by constructing three different scenarios which are characterized by different relationships (i.e., channel strength) between the agents. The scenarios used, involve two more specific types of agents: leaders and followers. Some agents have strong leadership abilities while others play a more timid role within the group. The general characteristics of leaders and followers as they were used in the experiments, which can be manifested differently within all agents, can be found in Table 5.2. The complete settings for the three scenarios can be found in Appendix A.

| Table 5.2. Parameters and state variables for leaders and followers |
|-----------------------------|-----------------------------|
| **Leader A**               | **Follower B**              |
| emotion level              | q_{OEA} high for particular O |
| intention level            | q_{OIA} high for particular O |
| expressivity               | \(\varepsilon_{SA}\) high | \(\varepsilon_{SB}\) low |
| channel strength           | \(\alpha_{SAB}\) high  | \(\alpha_{SAB}\) high \(\alpha_{SBA}\) low |
The different scenarios are depicted in Fig. 5.2. Scenario 1 consists of a group of agents in which agent1 has strong leadership abilities and high channel strengths with all other agents. His initial levels of emotion and intention for option A, are very high. Scenario 2 depicts a situation where there are two agents with leadership abilities in the group, agent1 and agent4. Agent1 has strong channel strength to agent2, while agent4 has a strong connection to agent3. Agent1 has an initial state of high (positive) emotion and intention for option A, while agent4 has strong emotion and intention states for option D. Agent2 and agent3 have show no strong intentions and emotions for any of the options in their initial emotion and intention states. In Scenario 3 there are no evident leaders. Instead, all agents have moderate channel strengths with each other. A majority of the agents (agent3 and agent4) prefers option C, i.e., initially they have high intention and emotions states for option C. For both scenarios two variants have been created, one with similar agent characteristics within the group (besides the difference between leader and follower characteristics), and the second with a greater variety of agent personalities. In this section, only the main results using the greater variety in agent characteristics are shown for the sake of brevity. For the formal verification (Section 5.6) both have been used.

The results of scenario 1 clearly show how one influential leader can influence the emotions and intention in a group. This is shown in the left graph of Fig. 5.3, here the z-axis shows the value for the respective states, and the x- and y-axes represent time and the various agents. The emotion and intention of the leader (in this case agent1) spread through the network of agents, while the emotions and intentions of other agents hardly spread. Consequently, the emotions and intentions for option A, which is the preferred option of the leader, develop to be high in all agents. As can be seen in the figure, there are small differences between the developments of emotions and intentions of the agents. This is because they have different personality characteristics, which are reflected in the settings for the scenario (see Appendix A). Depending on their openness, agents are more or less influenced.
by the states of others. Those agents with low openness (such as agent4) are hardly influenced by intentions and emotions of others.

In scenario 2 (as shown in the right graph of Fig. 5.3), the leader has somewhat positive emotions about option C as well, which explains the small but increasing spread of emotions (and after a while also intentions) concerning option C through the social network. Even though agent3 and agent2 both have a moderate intention for option B, their only strong channel strength is with each other, causing only some contagion between the two of them. Their intention does not spread because of a low expressive nature and low amplification rate of both agents. The patterns found in the simulation of scenario 2 are similar to the ones of scenario 1, with the addition that both leaders highly dominate the spread of the emotions and intentions. The figure shows that the emotions and intentions of agent2 turn out to depend highly on the emotions and intentions of agent1, whereas the emotions and intentions of agent3 highly depend on those of agent4. As can be seen in the figure, any preferences for option D and C by agent2 and agent3 quickly grow silent.
Scenario 3 shows how a group converges to the same high emotions and intentions for an option when there is no authority. In general, the graphs show that when there is no clear leadership, the majority determines the option with highest emotion and intentions in all agents. Option C, initially preferred by agent4 and agent3, eventually is the preferred option for all. However, the emotions and intentions for option A also spread and increase, though to a lesser extent. This is due to the fact that agent1 has strong feelings and intentions for option A and a high amplification level for these states. Furthermore, he has a significant channel strength with agent3, explaining why agent3 has the most increasing emotions and intentions for option A. However, the majority has the most important vote in this scenario.

Furthermore, some general statements can be made about the behaviour of the model. In case a leader has high emotions but low intentions for a particular option, both the intentions and emotions of all followers will increase for that option. On the other hand, if a leader has high intentions for a particular option, but not high emotions for that option, this intention will not spread to other agents.

5.6 Verification of Properties Specifying Emerging Patterns

This section addresses the analysis of the group decision making model by specification and verification of properties expressing dynamic patterns that emerge. The purpose of this type of verification is to check whether the model
behaves as it should, by automatically verifying such properties against the simulation traces for the various scenarios. In this way the modeller can easily detect inappropriate behaviours and locate sources of errors in the model. A typical example of a property that may be checked, is whether no unexpected situations occur, such as a variable running out of its bounds (e.g., \( q_A(t) > 1 \), for some time point \( t \) and agent \( A \)), or whether eventually an equilibrium value is reached, but also more detailed expected properties of the model such as compliance to the theories found in literature.

A number of dynamic properties have been identified, formalized in the Temporal Trace Language (TTL), cf. [6] and automatically checked. The TTL software environment includes a dedicated editor supporting specification of dynamic properties to obtain a formally represented temporal predicate logical language TTL formula. In addition, an automated checker is included that takes such a formula and a set of traces as input, and verifies automatically whether the formula holds for the traces. The language TTL is built on atoms referring to states of the world, time points and traces, i.e. trajectories of states over time. In addition, dynamic properties are temporal predicate logic statements that can be formulated with respect to traces based on a state ontology.

Below, a number of the dynamic properties that were identified for the group decision making model are introduced, both in semi-formal and in informal notation (where \( \text{state}(\gamma, t) |= p \) denotes that \( p \) holds in trace \( \gamma \) at time \( t \)). The first property counts the number of subgroups that are present. Here, a subgroup is defined as a group of agents having the same highest intention. Each agent has 4 intention values (namely one for each of the four options that exist), therefore the number of subgroups that can emerge are always: 1, 2, 3 or 4 subgroups.

**P1 – number of subgroups**
The number of subgroups in a trace \( \gamma \) is the number of options for which there exists at least one agent that has an intention for this option as its highest valued intention.

\[
P1_{\text{number of subgroups}}(\gamma:TRACE) \equiv \sum(I:\text{INTENTION}, \text{case}(\text{highest_intention}(\gamma, I), 1, 0))\]

where

\[
\text{highest_intention}(\gamma:TRACE, I:\text{INTENTION}) \equiv \exists A:AGENT \left[ \forall R1:REAL \ \text{state}(\gamma, t) |= \text{has_value}(A, I, R1) \Rightarrow \forall I2:\text{INTENTION} \neq I, \forall R2:REAL \ [\text{state}(\gamma, t) |= \text{has_value}(A, I2, R2) \Rightarrow R2 < R1] \right]
\]

In this property, the expression \( \text{case}(p, 1, 0) \) in TTL functions such that if property \( p \) holds it is evaluated to the second argument (1 in this example), and to the third argument (0 in this example) if the property does not hold. The sum operator simply adds these over the number of elements in the sort over which the sum is calculated (the intentions in this case). Furthermore, when \( \text{tb} \)
or $te$ are used in the property, they denote the begin or end time of the simulation, whereby in $te$ an equilibrium is often reached. Property P1 can be used to count the number of subgroups that emerge. A subgroup is defined as a group of agents that each have the same intention as their intention with highest value. This property was checked on multiple traces that each belong to one of the three scenario’s discussed in the simulation results section. For the traces for both variants of scenario 1, a single subgroup was found, for scenario 2: two subgroups were found, and for scenario 3, a single subgroup was found, which is precisely according to the expectations.

The second property counts the number of agents in each of the subgroups, using a similar construct.

**P2– subgroup size**
The number of agents in a subgroup for intention $I$ is the number of agents that have this intention as their highest intention.

$$P2\_\text{subgroup\_size}(\gamma:\text{TRACE}, I:\text{INTENTION}) \equiv \sum(A:\text{AGENT}, \text{case(highest\_intention\_for(\gamma, I, A), 1, 0)})$$

where

$$\text{highest\_intention\_for(\gamma:\text{TRACE}, I:\text{INTENTION}, A:\text{AGENT})} \equiv \forall R1:\text{REAL} \ [\text{state(\gamma, te)} \models \text{has\_level(A, I, R1)} \supset \forall I2:\text{OPTION} \neq I, \forall R2:\text{REAL} \ [\text{state(\gamma, te)} \models \text{has\_level(A, I2, R2)} \Rightarrow R2 < R1]$$

In the traces for scenario 1 the size of the single subgroup that occurred was 4 agents. For scenario 2 two subgroups of 2 agents were found. Finally, in scenario 3 only a single subgroup combining 4 agents has been found. These findings are correct; they indeed correspond to the simulation results.

The final property, P3, expresses that an agent is a leader in case its intention values have changed the least over the whole simulation trace, as seen from his initial intention values and compared to the other agents (thereby assuming that these agents moved towards the intention of the leader that managed to convince them of this intention).

**P3–leader**
An agent is considered a leader in a trace if the number of intentions for which it has the lowest change is at least as high as all other agents.

$$P3\_\text{leader}(\gamma:\text{TRACE}, A:\text{AGENT}) \equiv \forall A2:\text{AGENT} \neq A \\sum(I:\text{INTENTION}, \text{case(leader\_for\_intention(\gamma, A, I), 1, 0)}) \geq \sum(I:\text{INTENTION}, \text{case(leader\_for\_intention(\gamma, A2, I), 1, 0)})$$

where

$$\text{leader\_for\_intention(M:\text{TRACE}, A:\text{AGENT}, I:\text{INTENTION})} \equiv \forall R1, R2:\text{REAL} \ [\text{state(\gamma, tb)} \models \text{has\_value(A, I, R1) & state(\gamma, te)} \models \text{has\_value(A, I, R2)} \Rightarrow R2 < R1]$$
Using this definition, only agent 1 qualifies as a leader in scenario 1. For scenario 2 only agent 4 is a leader. Finally, in scenario 3 both agent 1 and agent 3 are found to be leaders as they both have equal intentions for which they change the least.

5.7 Modelling the Dynamics of Beliefs and Emotions in Groups

The agent-based social diffusion model introduced in Section 5.3 can be applied to both emotion and beliefs, but does not describe any interplay between diffusion of different states. For example, not only emotions of others, but also beliefs may affect emotions. On the other hand, strong emotions may affect personal characteristics for belief diffusion such as openness and expressivity. To incorporate such interactions, the basic model is extended as follows:

1. To update $q_{SA}$ for one state $S$, also the $q_{S'B}$ values for some other state $S'$ may be taken into account.
2. Some of the personal characteristics for a state $S$ may be determined dynamically depending on values $q_{S'B}$ for a certain other state $S'$.

The Effect of Emotion upon Belief

To model the effect of emotions on belief diffusion, below the personal characteristics $\delta_{SA}$, $\eta_{SA}$ and $\beta_{SA}$ for a belief state $S$ are not assumed constant, but are instead modeled in a dynamic manner, depending on emotions. As can be seen in the adopted model, multiple factors that influence diffusion of a state $S$ have been distinguished. One can divide these into three different categories: state $q_{SA}$, personal characteristics $\varepsilon_{SA}$, $\delta_{SA}$, $\eta_{SA}$ and $\beta_{SA}$ and interaction characteristic $\alpha_{BA}$. One additional category is introduced here, namely belief state characteristics $r_{SA}$ denoting how relevant, and $p_{SA}$ denoting how positive a belief state $S$ is for agent $A$. Examples of settings for an evacuation scenario can be found in Table 5.3.

The intensity of the emotional state of a person will affect his ability to receive information, thereby possibly affecting individual agent characteristics. In this case the focus is on one type of emotion, namely fear. A high level of fear contributes to the levels of $\beta_{SA}$, $\eta_{SA}$ and $\delta_{SA}$. However, if fear is low, the value of the parameters should be dominated by their initial values that represent the personal characteristics of the agent instead. First the effect of fear upon the
openness for a belief state \(S\) (characterized by a relevance \(r_{SA}\) and a positiveness \(p_{SA}\) for \(A\)) is expressed:

\[
\delta_{SA}(t+\Delta t) = \delta_{SA}(t) + \mu \cdot (1/1+e^{\sigma(q_{fear,A}(t)-\tau)}) \cdot [(1-(1-r_{SA})q_{fear,A}(t)) \cdot \delta_{SA}(t)] \cdot \Delta t
\]

(8)

Table 5.3 Types Of Information

<table>
<thead>
<tr>
<th>relevance for survival (r) [0-1]</th>
<th>positivity of information (p) [0-1]</th>
</tr>
</thead>
<tbody>
<tr>
<td>0</td>
<td>“The toilets are out of order”</td>
</tr>
<tr>
<td>1</td>
<td>“Local authorities have been informed”</td>
</tr>
<tr>
<td>1</td>
<td>“All rear exits are obstructed”</td>
</tr>
<tr>
<td>1</td>
<td>“The front emergency exit is clear”</td>
</tr>
</tbody>
</table>

If \(q_{fear,A}\) is lower than threshold \(\tau\) (on the interval \([0,1]\)), it will not contribute to the value of \(\delta_{SA}\). If \(q_{fear,A}\) has a value above \(\tau\), the openness will depend on the relevance of the information: when the relevance is high, openness will increase, while if the relevance is low, openness will decrease. In all formulae, \(\mu\) is an adaptation parameter. This proposed model corresponds to theories of emotions as frames for selective processing, as described in [17], [27]. A distinction between amplification values for different types of information is also made, depending on the emotional state fear. The dynamics for the characteristic \(\eta_{SA}(t)\) that model the amplification or absorption of belief state \(S\) are described as follows:

\[
\eta_{SA}(t+\Delta t) = 
\eta_{SA}(t) + \mu \cdot (1/1+e^{\sigma(q_{fear,A}(t)-\tau)}) \cdot (1-p_{SA}) \cdot (q_{fear,A}(t) - \eta_{SA}(t)) \cdot \Delta t
\]

(9)

The emotion of fear only has an influence when it is above the threshold. In that case the parameter only changes for relevant, non-positive information for which the parameter starts to move towards the value for the emotion of fear (meaning this type of belief will be amplified). This property represents an interpretation of [8] on how emotion can result in selective processing of emotion-relevant information.

The bias of an agent is also influenced by its emotion, but in addition depends on the content of the information, which can be either positive or negative:

\[
\beta_{SA}(t+\Delta t) = \beta_{SA}(t) + \mu \cdot (1/1+e^{\sigma(q_{fear,A}(t)-\tau)}) \cdot (1-q_{fear,A}(t)) \cdot (1-p_{SA}) \cdot \beta_{SA}(t) \cdot \Delta t
\]

(10)

Again, the bias is not influenced by fear if its value is low. In case fear is high, \(p_{SA}\) has a high impact on the bias: a low positiveness inhibits the bias, while a
high positiveness increases the bias. The agent thus has a bias towards negative belief in case it has a high level of fear, which corresponds with the narrowing hypothesis from Frederickson’s broaden-and-build theory in [17].

The Effect of Belief upon Emotion

After modeling the influence of emotion upon the belief contagion in the previous section, the opposite direction is investigated in this section: emotions being influenced by belief. This influence is modeled by altering the overall weighted impact of the contagion of the emotional state for fear. This is expressed as follows:

\[
q_{S_{\text{fear},A}} = v \cdot \left( \sum_{B \neq A} \gamma_{S_{\text{fear},B}} \cdot q_{S_{\text{fear},B}} / \gamma_{S_{\text{fear},A}} \right) + (1-v) \cdot \left( \sum_{S_{\text{info}}} \omega_{S_{\text{info},A}} \cdot (1-p_{S_{\text{info},A}}) \cdot r_{S_{\text{info},A}} \cdot q_{S_{\text{info},A}} \right)
\]

(11)

Table 5.4 Six scenarios for diffusion

<table>
<thead>
<tr>
<th>Initial settings</th>
<th>emotion → info</th>
<th>emotion ↔ info</th>
</tr>
</thead>
<tbody>
<tr>
<td>high fear levels</td>
<td>scenario 1</td>
<td>scenario 4</td>
</tr>
<tr>
<td>low fear levels</td>
<td>scenario 2</td>
<td>scenario 5</td>
</tr>
<tr>
<td>mixed fear levels</td>
<td>scenario 3</td>
<td>scenario 6</td>
</tr>
</tbody>
</table>

Here the influence depends on the impact from the emotion fear by others (the first factor, with weight \(v\)) in combination with the influence of the belief present within the agent. In this case, belief has an increasing effect on fear if it is relevant and non positive.

5.8 Simulation Results: Interaction Between Beliefs and Emotions

In order to see whether the approach indeed exhibits the patterns that can be expected from literature, a case study has been conducted in the domain of emergency evacuation. The states as shown in Table 5.4. have been used in combination with the emotion of fear. Furthermore, the value of the channel strength \(\alpha_{S_{BA}}\) has been made dependent upon the distance:

\[
\alpha_{S_{BA}} = 1 - \frac{1}{1 + e^{4\sigma(d_{AB} - \tau)}}
\]

(12)

This formula expresses that a belief is only perceived in case the distance between agent A and B \(d_{AB}\) is below the distance threshold \(\tau\).

The full model has been implemented in Matlab, and six different scenarios have been created (see Table 5.5). The complete settings for the three scenarios can be found in Appendix B.
In the scenarios, the emotional levels have been varied. The influence of belief upon emotion has been left out of to allow the sole analysis of the influence of emotions upon belief contagion. In each scenario, 4 agents have been used. The most important results are discussed below. Note that for all scenarios the value for the maximum distance ($\tau_{\text{distance}}$) has been set to 4, which represents that one can not hear or see a (non)verbal communication properly anymore when it is farther than the distance of 4. The threshold value for fear ($\tau_{\text{fear}}$) is set to 0.5.

### Table 5.5 Parameter Settings For Scenario 1

<table>
<thead>
<tr>
<th>Parameter</th>
<th>$q_{\text{fear}}$</th>
<th>$q_{\text{HH}}$</th>
<th>$q_{\text{HL}}$</th>
<th>$q_{\text{LH}}$</th>
<th>$q_{\text{LL}}$</th>
</tr>
</thead>
<tbody>
<tr>
<td>A1 (init $q$)</td>
<td>0.1</td>
<td>1</td>
<td>0.1</td>
<td>0.1</td>
<td>0.1</td>
</tr>
<tr>
<td>A2 (init $q$)</td>
<td>0.1</td>
<td>0.1</td>
<td>1</td>
<td>0.1</td>
<td>0.1</td>
</tr>
<tr>
<td>A3 (init $q$)</td>
<td>0.1</td>
<td>0.1</td>
<td>0.1</td>
<td>1</td>
<td>0.1</td>
</tr>
<tr>
<td>A4 (init $q$)</td>
<td>0.1</td>
<td>0.1</td>
<td>0.1</td>
<td>0.1</td>
<td>1</td>
</tr>
<tr>
<td>A1 ($\delta$)</td>
<td>0.5</td>
<td>0.5</td>
<td>0.5</td>
<td>0.5</td>
<td>0.5</td>
</tr>
<tr>
<td>A2 ($\delta$)</td>
<td>0.5</td>
<td>0.5</td>
<td>0.5</td>
<td>0.5</td>
<td>0.5</td>
</tr>
<tr>
<td>A3 ($\delta$)</td>
<td>0.5</td>
<td>0.5</td>
<td>0.5</td>
<td>0.5</td>
<td>0.5</td>
</tr>
<tr>
<td>A4 ($\delta$)</td>
<td>0.5</td>
<td>0.5</td>
<td>0.5</td>
<td>0.5</td>
<td>0.5</td>
</tr>
<tr>
<td>A1 ($\eta$)</td>
<td>0.5</td>
<td>0.3</td>
<td>0.3</td>
<td>0.3</td>
<td>0.3</td>
</tr>
<tr>
<td>A2 ($\eta$)</td>
<td>0.5</td>
<td>0.8</td>
<td>0.8</td>
<td>0.8</td>
<td>0.8</td>
</tr>
<tr>
<td>A3 ($\eta$)</td>
<td>0.5</td>
<td>0.1</td>
<td>0.1</td>
<td>0.1</td>
<td>0.1</td>
</tr>
<tr>
<td>A4 ($\eta$)</td>
<td>0.5</td>
<td>0.2</td>
<td>0.2</td>
<td>0.2</td>
<td>0.2</td>
</tr>
<tr>
<td>A1 ($\beta$)</td>
<td>0.5</td>
<td>0.1</td>
<td>0.1</td>
<td>0.1</td>
<td>0.1</td>
</tr>
<tr>
<td>A2 ($\beta$)</td>
<td>0.5</td>
<td>0.5</td>
<td>0.5</td>
<td>0.5</td>
<td>0.5</td>
</tr>
<tr>
<td>A3 ($\beta$)</td>
<td>0.5</td>
<td>0.9</td>
<td>0.9</td>
<td>0.9</td>
<td>0.9</td>
</tr>
<tr>
<td>A4 ($\beta$)</td>
<td>0.5</td>
<td>0.3</td>
<td>0.3</td>
<td>0.3</td>
<td>0.3</td>
</tr>
</tbody>
</table>

**Scenario 1.** First the general scenario and the interpretation of the values of the parameters is briefly described. In scenario 1, all agents initially are unaware of any danger and thus have low fear ($q_{\text{fear}} = 0.1$). Each agent has access to one out of four types of information (the four types can be made out of the four combinations of high/low relevance versus high/low positiveness of information). That is, agent 1 is located near the front exit and observes it is clear. Agent 2 just read on his phone that local authorities have been informed that there is smoke emerging from the building. Agent 3 just received word that all rear exits are blocked and agent 4 noticed that the toilets are out of order.
In order to clearly demonstrate the functioning of the model, all agents in this scenario have the same openness for all information and fear states (0.5) and they have the same amplification rate for fear (0.5). However, they differ in their amplification rate for information they receive. Agent 1, agent 3 and agent 4 all have relatively low amplification rates for all belief states, while agent 2 is more expressive and has a strong amplification for all belief states. In this scenario, agent 1 and agent 3 have a low bias for all types of belief and are not easily primed by it. Agent 2 has an average bias for all belief states and agent 3 is easily primed by any kind of belief. Details on the translation of this information into parameter settings can be found in Table 5.5. Fig. 5.5 shows the simulation results for scenario 1. The rows in the figure represent the various states: the first row shows values for the state fear \( (q_{\text{fear}}) \), row 2 represents the state of highly relevant, positive information \( (q_{\text{HH}}) \), row 3 of low relevant, positive information \( (q_{\text{LH}}) \), row 4 of highly relevant, negative information \( (q_{\text{HL}}) \) and row 5 shows values for the state of low relevant, negative information \( (q_{\text{LL}}) \). The columns represent the values for the state itself, and those for the openness, amplification, and bias for that state.

Analysis of the simulation results leads to the following conclusions. First, the perceived fear remains constant for all agents, since this scenario does not capture the influence of belief on emotion. The same holds for the individual values for openness, amplification and bias due to the fact that fear is so low that it does not influence the contagion of the belief. Second, all types of
information are quickly relayed to the other agents but after some time there is a slow decay of all types of belief.

**Scenario 2.** The only difference between scenario 1 and 2 is the initial level of fear, which is low for all agents in scenario 1, but high for all agents in scenario 2. In the simulation of scenario 2, which can be found in Fig. 5.6, different patterns emerge. Although the fear is still a constant factor, the high state of fear of all agents affects their values of openness, amplification and bias for particular belief states. For example, all values increase of the parameters for highly relevant, negative information. While the levels for positive information decrease or stay constant over time, the levels for negative information show a significant increase due to these changes of the parameters.

**Scenario 3.** In scenario 3 the agents all have different personalities and different levels of fear and belief, represented by different personal settings for all parameters. Simulation results show that due to the personal settings, some agents develop higher fear levels over time than others. See Fig. 5.7.
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Fig. 5.7. Simulation results of scenario 3

Fig. 5.8. The q-values for scenario 4 (leftmost column), 5 (center column), and 6 (rightmost column)
Scenario 4, 5, and 6. Simulations 4, 5 and 6 also take the influence of belief upon the level of fear into account. In these scenarios, the value for the weights of the influence of the belief state upon fear is set to 0.1, 0.7, 0.1, and 0.1 for $q_{HH}$, $q_{LH}$, $q_{HL}$, and $q_{LL}$ respectively. Furthermore, the value for $\nu$ has been set to 0.5. The initial settings of scenario 4, 5 and 6 are the same as scenario 1, 2 and 3, respectively. Since in the presented model the belief directly affects the emotion (and not the openness, amplification and bias), only the $q$-values will be discussed. They are displayed in Fig. 5.8. For the scenario with low fear (scenario 4) the $q_{fear}$ increases slightly for all agents due to availability of belief. However, just as the belief levels decay, the $q_{fear}$ levels decrease again after some time. More interesting are the results from scenario 5 and 6. The results of the simulation of scenario 5 show that (i) negative information - in particular relevant negative information - spreads quickly through the network of agents, and (ii) the spread of $q_{fear}$ first decreases and then spreads again causing an increase of this level for each of the agents. Note that the increase of $q_{HL}$ and, in a somewhat lesser extent, $q_{LL}$ cause the higher levels of $q_{fear}$. Looking at the simulation results of scenario 6 two main observations can be made. First, the $q_{fear}$ of agent 1, agent 3 and agent 4 does not increase as much as it did in scenario 5, due to the fact that they have lower values for negative information states than agent 2. Second, $q_{fear}$ is reduced as the agents obtain more positive information and soon after increases when the obtained information has a less positive content.

5.9 Mathematical Analysis of Equilibria and Monotonicity
In this section for the presented models a mathematical analysis will be discussed of equilibria, and monotonicity.

5.9.1 Mathematical analysis for the first model
During simulations it turns out that eventually equilibria are reached: all variables approximate values for which no change occurs anymore. Such equilibrium values can also be determined by mathematical analysis of the differential equations for the model:

\begin{align}
\frac{dq_{OEA}(t)}{dt} &= \gamma_{OEA} \cdot \left[ \eta_{OEA} \cdot (\beta_{OEA} \cdot (1 - (1-q_{OEA}(t))(1-q_{OEA}(t))) + (1-\beta_{OEA}) \cdot q_{OEA}(t) \cdot q_{OEA}(t)) + (1-\eta_{OEA}) \cdot q_{OEA}(t) \cdot (1-q_{OEA}(t)) \right] \cdot \Delta t \\
\frac{dq_{OLA}(t)}{dt} &= \gamma_{OLA} \cdot \left[ \eta_{OLA} \cdot (\beta_{OLA} \cdot (1 - (1-q_{OLA}(t))(1-q_{OLA}(t))) + (1-\beta_{OLA}) \cdot q_{OLA}(t) \cdot q_{OLA}(t)) + (1-\eta_{OLA}) \cdot q_{OLA}(t) \cdot (1-q_{OLA}(t)) \right] \cdot \Delta t
\end{align}

Putting $\frac{dq_{OEA}(t)}{dt} = 0$ and $\frac{dq_{OLA}(t)}{dt} = 0$ and assuming $\gamma_{OEA}$ and $\gamma_{OLA}$ nonzero, provides the following equilibrium equations for each agent $A$. 


\[ \eta_{\text{OEA}}(\beta_{\text{OEA}}(1-(1-q_{\text{OEA}}^*)(1-q_{\text{OEA}})) + (1 - \beta_{\text{OEA}}) q_{\text{OEA}}^* q_{\text{OEA}}) + (1 - \eta_{\text{OEA}}) q_{\text{OEA}}^* - q_{\text{OEA}} = 0 \]  
\[ \eta_{\text{OLA}}(\beta_{\text{OLA}}(1-(1-q_{\text{OLA}}^*)(1-q_{\text{OLA}})) + (1 - \beta_{\text{OLA}}) q_{\text{OLA}}^* q_{\text{OLA}}) + (1 - \eta_{\text{OLA}}) q_{\text{OLA}}^* - q_{\text{OLA}} = 0 \]  

For given values of the parameters \( \eta_{\text{OEA}}, \beta_{\text{OEA}}, \eta_{\text{OLA}}, \) and \( \beta_{\text{OLA}} \), these equations may be solved analytically or by standard numerical approximation procedures. Moreover, by considering when \( dq_{\text{OEA}}(t)/dt > 0 \) or \( dq_{\text{OEA}}(t)/dt < 0 \) one can find out when \( q_{\text{OEA}}(t) \) is strictly increasing and when strictly decreasing, and similarly for \( q_{\text{OLA}}(t) \). For example, for equation (2), one of the cases considered is the following.

Case \( \eta_{\text{OLA}} = 1 \) and \( \beta_{\text{OLA}} = 1 \)

For this case, equation (2) reduces to \( (1-(1-q_{\text{OLA}}^*)(1-q_{\text{OLA}})) - q_{\text{OLA}} = 0 \). This can easily be rewritten via \( (1- q_{\text{OLA}} ) - (1-q_{\text{OLA}}^*)(1-q_{\text{OLA}}) = 0 \) into \( q_{\text{OLA}}^* = 0 \).

Equilibrium: \( q_{\text{OLA}} = 1 \) or \( q_{\text{OLA}} < 1 \) and \( q_{\text{OEA}} = 0 \) and \( q_{\text{OIB}} = 0 \) for all \( B \neq A \) with \( \gamma_{\text{OBA}} > 0 \). Assuming both \( \omega_{\text{OLA}} \) and \( \omega_{\text{OEA}} \) nonzero, this results in the following:

strictly increasing: \( q_{\text{OLA}} < 1 \) and \( q_{\text{OEA}} > 0 \) or \( q_{\text{OIB}} > 0 \) for some \( B \neq A \) with \( \gamma_{\text{OBA}} > 0 \)

For a number of cases such results have been found, as summarised in Table 5.6. This table considers any agent \( A \) in the group. Suppose \( A \) is the agent in the group with highest \( q_{\text{OEA}} \), i.e., \( q_{\text{OEB}} \leq q_{\text{OEA}} \) for all \( B \neq A \). This implies that \( q_{\text{OEA}}^* = \sum_{B \neq A} \gamma_{\text{OBA}} \cdot q_{\text{OEB}} / \gamma_{\text{OEA}} = \sum_{B \neq A} \gamma_{\text{OBA}} \cdot q_{\text{OEA}} / \gamma_{\text{OEA}} = q_{\text{OEA}} \). Therefore \( q_{\text{OEA}}^* = q_{\text{OEA}} \) implies \( q_{\text{OEB}} = q_{\text{OEA}} \) for all \( B \neq A \) with \( \gamma_{\text{OBA}} > 0 \). Similarly, when \( A \) has the lowest \( q_{\text{OEA}} \) of the group, then always \( q_{\text{OEA}}^* \geq q_{\text{OEA}} \) and again \( q_{\text{OEA}}^* = q_{\text{OEA}} \) implies \( q_{\text{OEB}} = q_{\text{OEA}} \) for all \( B \neq A \) with \( \gamma_{\text{OBA}} > 0 \). This implies, for example, for \( \eta_{\text{OEA}} = 1 \) and \( \beta_{\text{OEA}} = 0.5 \), assuming nonzero \( \gamma_{\text{OBA}} \), that always for each option the
members’ emotion levels for option O will converge to one value in the group (everybody will feel the same about option O).

Table 6. Equilibria cases for an agent A with both $\omega_{OEA} > 0$, $\omega_{OLA} > 0$, and $\gamma_{OEBA} > 0$

<table>
<thead>
<tr>
<th>$\eta_{OEA}$</th>
<th>$\eta_{OLA}$</th>
<th>$\beta_{OEA}$</th>
<th>$\beta_{OLA}$</th>
<th>$\eta_{OIA}$</th>
<th>$\eta_{OIA}$</th>
<th>$\beta_{OIA}$</th>
<th>$\beta_{OIA}$</th>
</tr>
</thead>
<tbody>
<tr>
<td>$= 1$</td>
<td>$= 1$</td>
<td>$= 0.5$</td>
<td>$= 0$</td>
<td>$= 1$</td>
<td>$= 1$</td>
<td>$= 0$</td>
<td>$= 0$</td>
</tr>
<tr>
<td>$q_{OLA} = 1$</td>
<td>$q_{OEA} &lt; 1$</td>
<td>$q_{OIA} = 0$</td>
<td>$q_{OIB} = 0$</td>
<td>$q_{OEB} = 0$</td>
<td>$q_{OEC} = 0$</td>
<td>$q_{OEC} = 0$</td>
<td>$q_{OEC} = 0$</td>
</tr>
<tr>
<td>$q_{OEA} &lt; 1$</td>
<td>$q_{OEA} = 1$</td>
<td>$q_{OEA} &lt; 1$</td>
<td>$q_{OIA} = 0$</td>
<td>$q_{OIB} = 0$</td>
<td>$q_{OIB} = 0$</td>
<td>$q_{OIA} = 0$</td>
<td>$q_{OIA} = 0$</td>
</tr>
<tr>
<td>$q_{OEA} &gt; 0$</td>
<td>$q_{OEA} = 1$</td>
<td>$q_{OEA} &gt; 0$</td>
<td>$q_{OIA} = 1$</td>
<td>$q_{OIB} = 1$</td>
<td>$q_{OIB} = 1$</td>
<td>$q_{OIA} = 1$</td>
<td>$q_{OIA} = 1$</td>
</tr>
</tbody>
</table>
5.9.2 Mathematical analysis for the second model

In this section it is analyzed which are equilibria values that occur. In particular it is focused on the characteristics in the model and the fear state.

**Analysis of \( \delta_{\text{Sinfo}}(t) \), \( \beta_{\text{Sinfo}}(t) \) and \( \eta_{\text{Sinfo}}(t) \)**

The openness \( \delta_{\text{Sinfo}} \) is described in differential equation format by

\[
d\delta_{\text{Sinfo}}(t)/dt = \mu \delta_{\text{Sinfo}} (1/1 + e^{-\sigma (q_{\text{fear, A}} - \tau)}) \cdot [(1 - (1 - r_{\text{Sinfo A}}) q_{\text{fear, A}}(t)) - \delta_{\text{Sinfo}}(t)]
\]

It is assumed that \( \mu \delta_{\text{Sinfo}} > 0 \). First of all, it follows that when \( q_{\text{fear, A}} < \tau \), then always \( d\delta_{\text{Sinfo}}(t)/dt = 0 \), so for these cases any value for \( \delta_{\text{Sinfo}} \) is an equilibrium. Next, assuming \( q_{\text{fear, A}} \geq \tau \), it holds:

\[
\delta_{\text{Sinfo}} \text{ is in equilibrium} \quad \text{iff} \quad [(1 - (1 - r_{\text{Sinfo A}}) q_{\text{fear, A}}) - \delta_{\text{Sinfo}}(t)] = 0
\]

\[
\delta_{\text{Sinfo}} \text{ is strictly increasing} \quad \text{iff} \quad [(1 - (1 - r_{\text{Sinfo A}}) q_{\text{fear, A}}) - \delta_{\text{Sinfo}}(t)] > 0
\]

\[
\delta_{\text{Sinfo}} \text{ is strictly decreasing} \quad \text{iff} \quad [(1 - (1 - r_{\text{Sinfo A}}) q_{\text{fear, A}}) - \delta_{\text{Sinfo}}(t)] < 0
\]

From this the following equilibrium values can be determined (see also Table 5.7, upper part):

- \( q_{\text{fear, A}} < \tau \) and any value for \( \delta_{\text{Sinfo}}(t) \) or
- \( q_{\text{fear, A}} \geq \tau \) and \( \delta_{\text{Sinfo}} = 1 - (1 - r_{\text{Sinfo A}}) q_{\text{fear, A}} \)

For example, \( q_{\text{fear, A}} = 1 \Rightarrow \delta_{\text{Sinfo}}(t) = r_{\text{Sinfo A}} \) and \( r_{\text{Sinfo A}} = 1 \) and \( q_{\text{fear, A}} \geq \tau \Rightarrow \delta_{\text{Sinfo}} = 1 \). The following monotonicity conditions hold for \( q_{\text{fear, A}}(t) \geq \tau \):

\[
\delta_{\text{Sinfo}}(t) \text{ is strictly increasing} \quad \text{iff} \quad \delta_{\text{Sinfo}}(t) < 1 - (1 - r_{\text{Sinfo A}}) q_{\text{fear, A}}(t)
\]

\[
\delta_{\text{Sinfo}}(t) \text{ is strictly decreasing} \quad \text{iff} \quad \delta_{\text{Sinfo}}(t) > 1 - (1 - r_{\text{Sinfo A}}) q_{\text{fear, A}}(t)
\]

These conditions show that \( \delta_{\text{Sinfo}}(t) \) is attracted by the value \( 1 - (1 - r_{\text{Sinfo A}}) q_{\text{fear, A}}(t) \), so when \( q_{\text{fear, A}}(t) \) is stable, this value is a stable equilibrium for \( \delta_{\text{Sinfo}}(t) \). Similarly the equilibrium values of the characteristics \( \beta_{\text{Sinfo}} \) and \( \eta_{\text{Sinfo}} \) can be determined as shown in Table 5.7. Moreover, as above it can be shown that \( \beta_{\text{Sinfo}} \) is attracted by the value \( 1 - p_{\text{Sinfo}} \), and \( \eta_{\text{Sinfo}}(t) \) is attracted by the value \( q_{\text{fear, A}}(t) \), so they both are stable.

**Analysis of \( q_{\text{fear}}(A,t) \)**

The fear state is described by

\[
dq_{\text{fear}}(t)/dt = \gamma_A \cdot \{ \eta_{\text{Sfear}} \cdot (\beta_{\text{fear}} \cdot (1 - (1-q_{\text{fear}})^* \cdot (1-q_{\text{fear}})) + (1 - \beta_{\text{fear}}) \cdot q_{\text{fear}}^* + (1 - \eta_{\text{Sfear}}) \cdot q_{\text{fear}}^* - q_{\text{fear}} \}
\]
Then the equilibrium equations become:
\[ \eta_{SfearA} \cdot \beta_{SfearA} \cdot (1- (1-q_{SfearA}^*)) \cdot (1-q_{SfearA}) + (1 - \beta_{SfearA}) \cdot q_{SfearA}^* \cdot q_{SfearA} + (1 - \eta_{SfearA}) \cdot q_{SfearA}^* = q_{SfearA} \]

In general the equation is too complex to be solved symbolically, but for some cases it can be solved; see Table 5.7 (lower part).

**Special case** \( \eta_{SfearA} = 1 \) and \( \beta_{SfearA} = 1 \)
This case concerns an amplifying agent for fear with an increasing orientation. For this case the analysis shows that there is a strong tendency for \( q_{SfearA} \) to reach value 1. It will only not reach 1 if there are extreme circumstances that there is full absence of negative group impact: none of the other group members transfer any bad information or fear (see Table 5.7).

**Special case** \( \eta_{SfearA} = 1 \) and \( \beta_{SfearA} = 0 \)
This case concerns an amplifying agent for fear with a decreasing orientation. For this case the analysis shows that there is a strong tendency for \( q_{SfearA} \) to reach value 0. It will only not reach 0 if there are extreme circumstances in the sense that there is full presence of negative group impact: all other group members do transfer bad information and fear. See Table 5.7.

**Table 7** Equilibrium values. **UPPER**: values for \( q_{fear,A} \). **LOWER**: values for \( \delta_{Sinfo,A} \).

<table>
<thead>
<tr>
<th>( q_{fear,A} ) = 0</th>
<th>0 &lt; ( q_{fear,A} ) &lt; 1</th>
<th>( q_{fear,A} ) = 1</th>
</tr>
</thead>
<tbody>
<tr>
<td>( \eta_{Sfear} = 1 )</td>
<td>( \beta_{Sfear} = 1 )</td>
<td>any value &lt; 1 for ( q_{fear,A} ) iff there is full absence of negative group impact</td>
</tr>
<tr>
<td>( \eta_{Sfear} = 1 )</td>
<td>( \beta_{Sfear} = 0 )</td>
<td>( q_{fear,A} = 0 )</td>
</tr>
<tr>
<td>( \eta_{Sfear} = 0 )</td>
<td>( q_{fear,A} = 0 ), and there is full absence of negative group impact</td>
<td>( q_{SfearA}^* = q_{SfearA} ), ( q_{fear,A} = 1 ), and there is full presence of negative group impact</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>( q_{fear,A} ) = 1</th>
<th>( \tau \leq q_{fear,A} &lt; 1 )</th>
<th>( q_{fear,A} ) &lt; ( \tau )</th>
</tr>
</thead>
<tbody>
<tr>
<td>( \delta_{Sinfo} )</td>
<td>( \delta_{Sinfo} = r_{Sinfo} )</td>
<td>( \delta_{Sinfo} = 1 - (1 - r_{Sinfo}) \cdot \tau_{Sinfo} \cdot q_{fear,A} )</td>
</tr>
<tr>
<td>( \beta_{Sinfo} )</td>
<td>any value for ( \beta_{Sinfo} )</td>
<td>( \beta_{Sinfo} = 1 - p_{Sinfo} \cdot q_{fear,A} )</td>
</tr>
<tr>
<td>( \eta_{Sinfo} )</td>
<td>( r_{Sinfo} &gt; 0 ) and ( p_{Sinfo} &lt; 1 ) and ( \eta_{Sinfo} = q_{fear,A} )</td>
<td>any value for ( \eta_{Sinfo} )</td>
</tr>
</tbody>
</table>
Special case $\eta_{\text{SfearA}} = 0$

This case concerns an absorbing agent for fear. For this case the analysis shows that there is a strong tendency for $q_{\text{SfearA}}$ to reach some value between 0 and 1. It will only reach 0 or 1 if there are extreme circumstances that not any of the other group members does transfer any bad information or fear, or if all of them transfer both in a maximal sense. The value reached between 0 and 1 is some form of average of the values of the other group members.

Equilibria for $q_{\text{SfearA}}$

The equilibrium equation: $q_{\text{SfearA}}^* = q_{\text{SfearA}}$. For the cases $q_{\text{SfearA}}^* = q_{\text{SfearA}} = 0$ and $q_{\text{SfearA}}^* = q_{\text{SfearA}} = 1$ the terms of the double summation for $q_{\text{SfearA}}^*$ can be handled as above, thus providing the conditions as depicted in Table 5.7.

5.10 Discussion

In this chapter, an agent-based modelling approach has been presented, to model contagion of different types of individual agent states, which may have mutual interaction. First, a generic model for contagion of a single type of state was described. This generic model has been inspired by the neurological concept of mirroring (see e.g. [24], [30]). Previous emotion contagion models have been used as well as a source of inspiration (cf. [4], [5], [15], [16]). Emotion contagion, has been shown to occur in many cases varying from emotions in small groups to panicking crowds (cf. [1]). The generic model introduced unifies the models for emotion contagion and generalises to contagion of any type of individual state. The agent-based approach used differs from the approach of the computational models from social science such as in ([35], [22], [28]), which model the complex spread of innovations as diffusion that is asymmetric in time, irreversible, and nondeterministic. Next, two more specialised and more complex models were presented involving contagion of multiple types of states for which mutual interaction takes place.

As a first more complex model, a model was presented for the emergence of collective decision making in groups. In this model contagion of emotions and intentions and their interaction play a main role. The model has been based not only on the neurological concept of mirroring (see e.g. [24], [30]) but also on the Somatic Marker Hypothesis of Damasio (cf. [2], [10], [12], [13]). This provides an interaction between the two types of states, in the form of influences of emotions upon intentions. Several scenarios have been simulated by the model to investigate the emerging patterns, and also to look at leadership of agents within groups. The results of these simulation experiments show patterns as desired and expected. In order to be able to make this claim more solid, a formal verification of the simulation traces have been performed,
showing that the model indeed behaves properly. By a mathematical analysis, equilibria of the model have been determined.

As a second more complex model, a model has been presented which incorporates the effect of emotions upon the spreading of belief as well as the effect of belief upon emotions. This work has been inspired by a number of theories and observations as found in literature (cf. [1], [7], [8], [17], [27], [37]). The model has been evaluated by a case study in the domain of emergency evacuations, and was shown to exhibit the patterns that could be expected based upon the literature. Also for this model by a mathematical analysis equilibria have been determined.

For future work, an interesting element will be to scale up the simulations and investigate the behaviour of agents in larger scale simulations. Furthermore, modelling a more detailed neurological model is also part of future work, thereby defining an abstraction relation mapping between this detailed level model and the current model. As part of further work it can also be considered to model how mood can affect (systematic) information processing, for example in case of a depression. In [9] such mechanisms are discussed. Other ideas for future work consist of extending the current model for multiple emotions affecting each other and beliefs as well and vice versa. Moreover, models addressing contagion of more than two different types of states and their interaction will be addressed.

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References


Part III: Integrated Modelling of Social Contagion and Internal Dynamics


Chapter 6 - Modelling Collective Decision Making in Groups and Crowds: Integrating Social Contagion and Interacting Emotions, Beliefs and Intentions

Tibor Bosse, Mark Hoogendoorn, Michel C.A. Klein, Jan Treur, C. Natalie van der Wal, Arlette van Wissen

Abstract
Collective decision making involves on the one hand individual mental states such as beliefs, emotions and intentions, and on the other hand interaction with others with possibly different mental states. Achieving a satisfactory common group decision on which all agree requires that such mental states are adapted to each other by social interaction. Recent developments in Social Neuroscience have revealed neural mechanisms by which such mutual adaptation can be realised. These mechanisms not only enable intentions to converge to an emerging common decision, but at the same time enable to achieve shared underlying individual beliefs and emotions. This chapter presents a computational model for such processes. As an application of the model, an agent-based analysis was made of patterns in crowd behaviour, in particular to simulate a real-life incident that took place on May 4, 2010 in Amsterdam. From available video material and witness reports, useful empirical data were extracted. Similar patterns were achieved in simulations, whereby some of the parameters of the model were tuned to the case addressed, and most parameters were assigned default values. The results show the inclusion of contagion of belief, emotion, and intention states of agents results in better reproduction of the incident than non-inclusion.

Parts of this chapter appeared as:

6.1 Introduction

When it comes to group decision making versus individual decision making, it is often said that ‘two heads are better than one’, and ‘the more the merrier’. Combining the individual capabilities in a group setting is often perceived as a benefit for all parties involved. However, deciding as a group comes with substantial challenges, as each group member has autonomous neurological processes, carrying, for example, private mental states such as emotions, beliefs, and intentions, which may seem hard to combine within a group. So, viewed from a distance, group decision making by reaching mutual agreement could be very hard. Yet, quite often coherent decisions are made by groups, and group members even seem to feel good with these decisions. In recent years, this seeming paradox has been resolved by developments in the new area called Social Neuroscience; e.g., [4], [5], [12], [13], [16].

The crux is that these private mental states are not so static and isolated as they may seem; they often show high extents of dynamics due to social interaction. In Social Neuroscience neural mechanisms have been discovered that indeed - often in unconscious manners - account for mutual mirroring effects between mental states of different persons; e.g., [20], [25], [29]. For example, an emotion expresses itself in a smile which, when observed by another person, automatically triggers certain preparation neurons (also called mirror neurons) for smiling within this other person, and consequently generates the same emotion. Similarly, mirroring of intentions and beliefs can be considered.

In this chapter group decision making in stressful circumstances (with emergency evacuations as an example) is addressed. In these circumstances, emotions have an important interaction with the beliefs and intentions involved in a decision making process. Based on findings from neuroscience (Section 6.2), the computational model ASCRIBE (for Agent-based Social Contagion Regarding Intentions, Beliefs and Emotions) is introduced that not only incorporates mechanisms for mirroring emotions, intentions and beliefs between different persons (Section 6.3), but also addresses how within a person beliefs and emotions affect each other, and how they both affect the person’s intentions (Section 6.4). A number of examples simulations have been performed (Section 6.5).

As a case study the model was evaluated based on empirical data for crowd behaviour. Behavioural patterns emerging in large crowds are often difficult to regulate. Various examples have shown how things can easily get out of control when many people come together during big events. Especially within crowds, the consequences can be devastating when emotion spirals (e.g., for aggression or fear) develop to high levels. In Sections 6.6 to 6.9, a computational analysis is presented of the incident that happened on Dam square in Amsterdam at the 4th of May in 2010,
when large numbers gathered for the national remembrance of the dead (‘dodenherdenking’). In the middle of a two-minute period of silence, one person started shouting, causing panic to occur among the people present. What happened there, as a result of a panic spiral, was a relatively mild incident in which ‘only’ a number of persons ended up in hospitals with fractures and bruises. ASCRIBE was extended to incorporate this crowd movement context (Section 6.7). To tune the latter model to specific characteristics, a specific automated parameter tuning method was used (Section 6.8). It is shown how the model is able to simulate this outburst of panic and its consequences (Section 6.9). Finally, the model is compared to an epidemiological model in Section 6.10, and Section 6.11 concludes the chapter with a discussion.

6.2 Background from Social Neuroscience

Within Neuroscience it has been discovered that certain neurons have a mirroring function (e.g., [11], [20], [21], [25], [26], [27], [28], [29]). In the context of the neural circuits in which they are embedded, these neurons show both a function in preparation for certain actions or bodily changes and a function to mirror similar states of other persons: they are active also when the person observes somebody else intending or performing the action or body change. This includes expressing emotions in body states, such as facial expressions. These neurons and the neural circuits in which they are embedded play an important role in social functioning (e.g., [11], [20], [25], [29]). When mental states of other persons are mirrored by some of the person’s own states, which at the same time play a role in generating their own behaviour, then this provides an effective basic mechanism for persons to fundamentally affect each other’s mental states and behaviour. These discoveries are the basis for an exciting new research area, called Social Neuroscience.

A person’s cognitive states usually induce emotions, as described by neurologist Damasio, [8], [9]; for example:

‘Even when we somewhat misuse the notion of feeling — as in “I feel I am right about this” or “I feel I cannot agree with you” — we are referring, at least vaguely, to the feeling that accompanies the idea of believing a certain fact or endorsing a certain view. This is because believing and endorsing cause a certain emotion to happen.’ ([9], p. 93).

Damasio’s Somatic Marker Hypothesis, cf. [1], [7], [9], [10], is a theory on decision making which provides a central role to emotions felt. Within a given context, each represented decision option induces (via an emotional response) a feeling which is used to mark the option. For example, a strongly negative somatic
marker linked to a particular option occurs as a strongly negative feeling for that option. Similarly, a positive somatic marker occurs as a positive feeling for that option ([7], pp. 173-174).

In Figure 6.1 an overview of the interplay of the different states within the model for collective decision making is shown.

![Figure 6.1. The interplay of beliefs, emotions and intentions in social context](image)

It is assumed that at the individual level the strength of an intention for a certain decision option depends on the person’s beliefs (cognitive responding) and emotions (somatic marking) in relation to that option. Moreover, it is assumed that beliefs may generate certain emotions (affective responding), for example fear, that in turn may affect the strength of beliefs (affective biasing). Note that it is assumed that these latter emotions are independent of the different decision options. Given this, to obtain collectiveness of the decision making a mirroring mechanism as briefly described above is used in three different ways; see also Figure 6.1 and Table 6.1:

- **mirroring of emotions** is a mechanism for how fear and emotions felt in different individuals about a certain considered decision option mutually affect each other,
- **mirroring of beliefs** is a mechanism transferring information on the extent to which different individuals believe certain information
- **mirroring of intentions** is a mechanism transferring information between individuals on the strength of action tendencies (e.g., [15], p.70) for certain decision options

These mechanisms describe not only how over time the individual decision intentions of group members may converge to a common group intention, but also how this relates to a basis of shared beliefs and shared emotions
developed within the group. Indeed, the computational model introduced in Sections 6.3 and 6.4 shows these types of patterns, as illustrated in Section 6.5.

<table>
<thead>
<tr>
<th>From</th>
<th>To</th>
<th>Agent</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>belief</td>
<td>emotion</td>
<td>intra-</td>
<td>affective response on information; for example, on threats and possibilities to escape</td>
</tr>
<tr>
<td>emotion</td>
<td>emotion</td>
<td>inter-</td>
<td>emotion mirroring by nonverbal and verbal interaction; for example, fear contagion</td>
</tr>
<tr>
<td>emotion</td>
<td>belief</td>
<td>intra-</td>
<td>affective biasing; for example, adapting openness, amplification extent and orientation</td>
</tr>
<tr>
<td>belief</td>
<td>belief</td>
<td>inter-</td>
<td>belief mirroring by nonverbal and verbal interaction; for example, diffusion of information on threats and possibilities to escape</td>
</tr>
<tr>
<td>belief</td>
<td>intention</td>
<td>intra-</td>
<td>cognitive response on information; for example, aiming for an exit that is believed to be reachable</td>
</tr>
<tr>
<td>emotion</td>
<td>intention</td>
<td>intra-</td>
<td>somatic marking of intention options; for example, giving options that feel bad a low valuation</td>
</tr>
<tr>
<td>intention</td>
<td>intention</td>
<td>inter-</td>
<td>intention mirroring by nonverbal and verbal interaction; for example, contagion of tendency to go in a certain direction</td>
</tr>
</tbody>
</table>

### 6.3 A Computational Model for Mirroring of Mental States

A main building block of the computational model is a general model describing at an abstract level the mirroring of a given mental state \( S \) (for example, an emotion, belief or intention). This is based upon the model that was also used as a generic building block in [18], [19]. An important element is the contagion strength \( \gamma_{SB} \) from person \( B \) to person \( A \) in a group. This denotes how much the state \( S \) of \( A \) is influenced by the state \( S \) of \( B \). It is defined by

\[
\gamma_{SB} = \varepsilon_{SB} \alpha_{SB} \delta_{SA}
\]

Here, \( \varepsilon_{SB} \) is the personal characteristic \textit{expressiveness} of the sender \( B \) for \( S \), \( \delta_{SA} \) the personal characteristic \textit{openness} of the receiver \( A \) for \( S \), and \( \alpha_{SB} \) the interaction characteristic \textit{channel strength} for \( S \) from sender \( B \) to receiver \( A \). In order to determine the level \( q_{SA} \) of state \( S \) in an agent \( A \), the following calculations are performed. First, the overall contagion strength \( \gamma_{SA} \) from the group towards agent \( A \) is calculated:
\[ \gamma_{SA} = \sum_{B \neq A} \gamma_{SB,A} \] (2)

This value is used to determine the weighed impact \( q_{SA}^* \) of all the other agents upon state \( S \) of agent \( A \):

\[ q_{SA}^*(t) = \sum_{B \neq A} \gamma_{SB,A} q_{Sb}(t) / \gamma_{SA} \] (3)

The dynamics of the different mechanisms involved are modelled by dynamical relationships using the following general pattern:

\[ Y_A(t+\Delta t) = Y_A(t) + \gamma \text{ <change_expression>} \Delta t \]

Here the change of \( Y \) is specified for a time interval between \( t \) and \( t + \Delta t \); the \( \gamma \) represents the speed of the adjustment processes. Applied to the variable \( q_{SA}(t) \) for \( Y_A(t) \) the following is taken:

\[ \text{<change_expression>} = f(q_{SA}^*(t), q_{SA}(t)) - q_{SA}(t) \]

where \( f(q_{SA}^*(t), q_{SA}(t)) \) is a combination function. Therefore for the case considered:

\[ q_{SA}(t+\Delta t) = q_{SA}(t) + \gamma_{SA} \left[ f(q_{SA}^*(t), q_{SA}(t)) - q_{SA}(t) \right] \Delta t \] (4)

Two additional personal characteristics determine how much this external influence actually changes state \( S \) of agent \( A \), namely the tendency \( \eta_{SA} \) to absorb or to amplify the level of a state and the bias \( \beta_{SA} \) towards increasing (upward) or reducing (downward) impact for the value of the state. Based on this the combination function \( f(q_{SA}^*(t), q_{SA}(t)) \) used was taken as:

\[ f(q_{SA}^*(t), q_{SA}(t)) = \eta_{SA} \left[ \beta_{SA} (1 - (1 - q_{SA}^*(t))(1 - q_{SA}(t))) \right. \\
+ (1 - \beta_{SA}) q_{SA}^*(t) q_{SA}(t) \left. \right] + (1 - \eta_{SA}) q_{SA}^*(t) \]

By (4) the new value for the state \( S \) at time \( t + \Delta t \) is calculated from the old value at \( t \), plus the change of the value based upon the transfer by mirroring. This change is defined as the multiplication of the overall contagion strength \( \gamma_{SA} \) times the difference of a combination function of \( q_{SA}^* \) and \( q_{SA} \) with \( q_{SA} \). The combination function used has a component for amplification (after \( \eta_{SA}(t) \)) and one for absorption. The amplification component depends on the tendency of the person towards more positive (part multiplied by \( \beta_{SA}(t) \) or
negative (part of equation multiplied by $1 - \beta_{SA}(t)$ side). Table 6.2 summarizes the most important parameters and states within this general model.

Table 6.2. Parameters and states

<table>
<thead>
<tr>
<th>$q_{SA}$</th>
<th>level for state $S$ for person $A$</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\varepsilon_{SA}$</td>
<td>extent to which person $A$ expresses state $S$</td>
</tr>
<tr>
<td>$\delta_{SA}$</td>
<td>extent to which person $A$ is open to state $S$</td>
</tr>
<tr>
<td>$\eta_{SA}$</td>
<td>tendency of person $A$ to absorb or amplify state $S$</td>
</tr>
<tr>
<td>$\beta_{SA}$</td>
<td>positive or negative bias of person $A$ on state $S$</td>
</tr>
<tr>
<td>$\alpha_{SB,\gamma}$</td>
<td>channel strength for state $S$ from sender $B$ to receiver $A$</td>
</tr>
<tr>
<td>$\gamma_{SB,\gamma}$</td>
<td>contagion strength for $S$ from sender $B$ to receiver $A$</td>
</tr>
</tbody>
</table>

Table 6.3. The different types of processes in the model

<table>
<thead>
<tr>
<th>From $S$</th>
<th>To $S'$</th>
<th>Type</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>belief($X$)</td>
<td>fear</td>
<td>internal</td>
<td>affective response on information; for example, on threats and possibilities to escape</td>
</tr>
<tr>
<td>emotion($O$)</td>
<td>emotion($O$)</td>
<td>interaction</td>
<td>emotion mirroring by nonverbal and verbal interaction; for example, fear contagion</td>
</tr>
<tr>
<td>fear</td>
<td>belief($X$)</td>
<td>internal</td>
<td>affective biasing; for example, adapting openness, amplification extent and orientation</td>
</tr>
<tr>
<td>belief($X$)</td>
<td>belief($X$)</td>
<td>interaction</td>
<td>belief mirroring by nonverbal and verbal interaction; for example, of information on threats and options to escape</td>
</tr>
<tr>
<td>belief($X$)</td>
<td>intention($O$)</td>
<td>internal</td>
<td>cognitive response on information; for example, aiming for an exit that is believed to be reachable</td>
</tr>
<tr>
<td>emotion($O$)</td>
<td>intention($O$)</td>
<td>internal</td>
<td>somatic marking of intention options; for example, giving options that feel bad a low valuation</td>
</tr>
<tr>
<td>intention($O$)</td>
<td>intention($O$)</td>
<td>interaction</td>
<td>intention mirroring by nonverbal and verbal interaction; for example, of tendency to go in a certain direction</td>
</tr>
</tbody>
</table>

6.4 Modelling the Interplay of Beliefs, Emotions and Intentions

This section describes a computational model for the interplay of emotions, beliefs and intentions in a group of persons in the context of collective decision making. In this model the general model described in Section 6.3 is specialized for three different types of mental states $S$, namely beliefs, emotions, and intentions. In principle this is a large number of variants of
equation (4) above for all persons \( A \) in a group and all states \( S \), indicated by \( belief(X) \), \( fear \), \( emotion(O) \), \( intention(O) \) for information \( X \) and options \( O \).

However, in addition, at the individual level interactions between these different states are modelled, as depicted in Figure 6.1; see also Table 6.1 for a brief explanation of all interactions in the model. This means that the model obtained by forming specializations of the generic model from Section 6.3 is modified in order to incorporate the internal interactions between the different types of states. For example, as can be seen in Table 6.3, the effect of beliefs on fear of a person has to be combined with the effect of fear of other group members on the own fear. This will be explained in more detail in the remainder of this section.

### 6.4.1 The Effect of Emotions on Beliefs

To model the effect of emotions on information diffusion, below the personal characteristics \( \delta_{S,A} \), \( \eta_{S,A} \) and \( \beta_{S,A} \) for a belief state \( S = belief(X) \) are not assumed constant, but are instead modeled in a dynamic manner, depending on emotions. Personal characteristics \( \epsilon_{belief(X)A} \), \( \delta_{belief(X)A} \), \( \eta_{belief(X)A} \), \( \beta_{belief(X)A} \) and interaction characteristic \( \alpha_{belief(X)BA} \) are parameters in the model as described in Section 6.3. One additional category is introduced here, namely informational state characteristics \( r_{XA} \) denoting how relevant, and \( p_{XA} \) denoting how positive information \( X \) is for person \( A \). An assumption made for the model is that the intensity of the fear state of a person will affect his ability to receive information, by affecting the value of the individual person characteristics; in particular, a high level of fear affects \( \beta_{belief(X)A} \), \( \eta_{belief(X)A} \) and \( \delta_{belief(X)A} \). First the effect of fear upon the openness for a belief \( belief(X) \) (characterized by a relevance \( r_{XA} \) of information \( X \) for \( A \)) is expressed:

\[
\delta_{belief(X)A}(t+\Delta t) = \delta_{belief(X)A}(t) + \mu \cdot \left(1/1+e^{-\sigma(q_{fear,A}(t) - \tau)}\right) \cdot \left[(1 - (1-r_{XA}) q_{fear,A}(t) ) \delta_{belief(X)A}(t) \right] \cdot \Delta t
\]

If \( q_{fear,A} \) is lower than threshold \( \tau \) (on the interval \([0,1]\)), it will not contribute to the value of \( \delta_{belief(X)A} \). If \( q_{fear,A} \) has a value above \( \tau \), the openness will depend on the relevance of the information: when the relevance is high, openness will increase, while if the relevance is low, openness will decrease. In all formulae, \( \mu \) is an adaptation parameter. This proposed model corresponds to theories of emotions as frames for selective processing, as described in [14], [23]. A distinction between amplification values for different types of information is also made, depending on the emotional state fear. The dynamics for the characteristic \( \eta_{belief(X)A}(t) \) modeling the amplification or absorption of \( belief(X) \) are described as follows:
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\[ \eta_{\text{belief}(X)A}(t+\Delta t) = \eta_{\text{belief}(X)A}(t) + \mu \cdot \left( \frac{1}{1+e^{\sigma q_{\text{fear,A}}(t) - \tau}} \cdot \left[ r_{\text{fear,A}} \cdot (1-p_{\text{fear,A}}) \cdot (q_{\text{fear,A}}(t) \cdot \eta_{\text{belief}(X)A}(t)) \right] \right) \cdot \Delta t \]  

(6)

The emotion of fear only has an influence when it is above the threshold. In that case the parameter only changes for relevant, non-positive information for which the parameter starts to move towards the value for the emotion of fear (meaning this type of information will be amplified). This property represents an interpretation of [6] on how emotion can result in selective processing of emotion-relevant information.

The bias of a person is also influenced by its emotion, but in addition depends on the content of the information, which can be either positive or negative:

\[ \beta_{\text{belief}(X)A}(t+\Delta t) = \beta_{\text{belief}(X)A}(t) + \mu \cdot \left( \frac{1}{1+e^{\sigma q_{\text{fear,A}}(t) - \tau}} \right) \cdot \left[ (\zeta \cdot p_{\text{XA}} + (1-\zeta) \cdot (1-p_{\text{fear,A}})) - \beta_{\text{belief}(X)A}(t) \right] \cdot \Delta t \]  

(7)

Parameter \( \tau \) is a number between 0 and 1 and represents a threshold for \( q_{\text{fear}} \): when \( q_{\text{fear}} > \tau \), then \( q_{\text{fear,A}} \) has an influence on the bias \( \beta_{\text{belief}(X)A}(t) \). Parameter \( \zeta \) is a personality characteristic; if \( \zeta = 1 \), represents a person who is optimistic when he/she has a lot of fear: positive information will be strengthened more and negative information will be weakened more. The reverse happens when \( \zeta = 0 \), this represents a person who is more ‘pessimistic’ when experiencing fear: negative information will be strengthened and positive information will be weakened. Both personality characteristics seem to exist in people: a bias towards the negative side of information in case of experiencing a high level of fear, corresponds with the narrowing hypothesis from Frederickson’s broaden-and-build theory in [44]. Others have a bias towards more positive information and emotions. Leaders could use this ability motivate their followers in times of crisis, as positive information and emotions broaden people’s mindset [14], and focusing on positive information and emotions can contribute positively to individual’s mental states (including attention and cognitive capacity) and resources [44]. The dynamically changing ‘parameters’ \( \delta_{\text{belief}(X)A}(t), \eta_{\text{belief}(X)A}(t), \beta_{\text{belief}(X)A}(t) \) are used in the equation describing the dynamics of the belief state \( \text{belief}(X) \):

\[ q_{\text{belief}(X)A}(t+\Delta t) = q_{\text{belief}(X)A}(t) + \gamma_{\text{belief}(X)A}(t) \left[ f(q_{\text{belief}(X)A}(t), q_{\text{belief}(X)A}(t)) - q_{\text{belief}(X)A}(t) \right] \Delta t \]  

(8)
where the combination function \( f(q_{SA^*}(t), q_{SA}(t)) \) used is taken in a dynamic manner as:

\[
f(q_{belief(X)A^*}(t), q_{belief(X)A}(t)) = \eta_{belief(X)A}(t) \left[ \beta_{belief(X)A}(t) (1 - (1 - q_{belief(X)A^*}(t))(1 - q_{belief(X)A}(t))) + (1 - \beta_{belief(X)A}(t)) q_{belief(X)A^*}(t) q_{belief(X)A}(t) \right] + (1 - \eta_{belief(X)A}(t)) q_{belief(X)A^*}(t)
\]

Note that since it depends on \( \delta_{belief(X)A}(t) \), also \( \gamma_{belief(X)A}(t) \) becomes dynamic.

### 6.4.2 The Effect of Beliefs on Emotions in the Dynamics of Fear

Besides modeling the influence of emotion upon the information contagion in the previous Section, the opposite direction is investigated in this Section: emotions being influenced by information. This influence is modeled by altering the overall weighed impact of the contagion of the emotional state for fear. This is expressed as follows:

\[
q_{fear,A^*}(t) = \nu_A \cdot \left( \sum_{B \neq A} \gamma_{fearBA} \cdot q_{fearB} / \gamma_{fear,A} \right) + (1 - \nu_A) \cdot \left( \sum_X \omega_{X,fear,A} \cdot (1 - p_{XA}) \cdot r_{XA} \cdot q_{belief(X)A} \right)
\]

Here the influence depends on the impact from the emotion fear by others (the first factor, with weight \( \nu_A \)) in combination with the influence of the belief present within the person. In this case, information has an increasing effect on fear if it is relevant and non-positive. This \( q_{fear,A^*}(t) \) is used in the equation describing the dynamics of fear:

\[
q_{fear,A}(t+\Delta t) = q_{fear,A}(t) + \gamma_{fear,A} \left[ f(q_{fear,A^*}(t), q_{fear,A}(t)) - q_{fear,A}(t) \right] \Delta t
\]

with

\[
f(q_{fear,A^*}(t), q_{fear,A}(t)) = \eta_{fear,A} \left[ \beta_{fearA} (1 - (1 - q_{fear,A^*}(t))(1 - q_{fear,A}(t))) + (1 - \beta_{fearA}) q_{SA^*}(t) q_{SA}(t) \right] + (1 - \eta_{fear,A}) q_{fear,A^*}(t)
\]

### 6.4.3 The Effects of Beliefs and Emotions on Intentions

The abstract model for mirroring described above applies to emotion, belief and intention states \( S \) for an option \( O \) or the situation in general, but does not describe any interplay for intentions yet. Taking the Somatic Marker Hypothesis on decision making as a point of departure, not only intentions of others, but also own emotions affect the own intentions. To incorporate such
an interaction, the basic model is extended as follows: to update $q_{\text{intention}(O)A}(t)$ for an intention state $S$ relating to an option $O$, both the intention states of others for $O$ and the $q_{\text{emotion}(O)A}(t)$ values for the emotion state $S'$ for $O$ are taken into account. These intention and emotion states $S$ and $S'$ for option $O$ are denoted by $OI$ and $OE$, respectively:

- Level of fear of person $A$: $q_{\text{fear}(A)}(t)$
- Level of emotion for option $O$ of person $A$: $q_{\text{emotion}(O)A}(t)$
- Level of intention indication for option $O$ of person $A$: $q_{\text{intention}(O)A}(t)$
- Level of belief supporting option $O$ of person $A$: $q_{\text{belieffor}(O)A}(t)$

Here $q_{\text{belieffor}(O)A}(t)$ denotes to aggregated support for option $O$ by beliefs of $A$; it is defined as

$$q_{\text{belieffor}(O)A}(t) = \sum_X \omega_{XOA} q_{\text{belief}(X)A(t)} / \sum_X \omega_{XOA}$$

where $\omega_{XOA}$ indicates how supportive information $X$ is for option $O$. The combination of the own (positive) emotion level and the rest of the group’s aggregated intention is made by a weighted average of the two:

$$q_{\text{intention}(O)A}**(t) = (\omega_{OIA1}/\omega_{OIEBA}) q_{\text{intention}(O)A}(t) + (\omega_{OEA2}/\omega_{OIEBA}) q_{\text{emotion}(O)A}(t) + (\omega_{OBA2}/\omega_{OIEBA}) q_{\text{belieffor}(O)A}(t)$$

$$\gamma_{\text{intention}(O)A}** = \omega_{OIEBA} \gamma_{\text{intention}(O)A}$$

where $\omega_{OIA1}$, $\omega_{OBA2}$ and $\omega_{OEA2}$ are the weights for the contributions of the group intention impact (by mirroring), the own emotion impact (by somatic marking), and the own belief impact on the intention of $A$ for $O$, respectively, and

$$\omega_{OIEBA} = \omega_{OIA1} + \omega_{OEA2} + \omega_{OBA2}$$

The combination of the own belief level and the rest of the group’s aggregated emotion for a certain option $O$ is made by a weighted average of the two:

$$q_{\text{emotion}(O)A}**(t) = (\omega_{OEA1}/\omega_{OIEBA}) q_{\text{emotion}(O)A}(t) + (\omega_{OBA1}/\omega_{OIEBA}) q_{\text{belieffor}(O)A}(t)$$

$$\gamma_{\text{emotion}(O)A}** = \omega_{OIEBA} \gamma_{\text{emotion}(O)A}$$

where $\omega_{OEA1}$ and $\omega_{OBA1}$ are the weights for the contributions of the group emotion impact (by mirroring), the own belief impact on the emotion of $A$ for
0, respectively, and \( \omega_{OEBA} = \omega_{OEAI} + \omega_{OBAI} \). Then the overall model for the dynamics of emotions and intentions for options becomes:

\[
q_{\text{emotion}(O)A}(t + \Delta t) = q_{\text{emotion}(O)A}(t)
+ \gamma_{\text{intention}(O)A} \left[ \eta_{\text{emotion}(O)A} \left( \beta_{\text{emotion}(O)A} (1 - (1-q_{\text{emotion}(O)A}(t))(1-q_{\text{emotion}(O)A}(t))))
+ (1-\beta_{\text{emotion}(O)A}) q_{\text{emotion}(O)A}(t) \right)
+ (1 - \eta_{\text{emotion}(O)A}) q_{\text{emotion}(O)A}(t) - q_{\text{emotion}(O)A}(t) \right] \cdot \Delta t
\]

\[
q_{\text{intention}(O)A}(t + \Delta t) = q_{\text{intention}(O)A}(t)
+ \gamma_{\text{intention}(O)A} \left[ \eta_{\text{intention}(O)A} \left( \beta_{\text{intention}(O)A} (1 - (1-q_{\text{intention}(O)A}(t))(1-q_{\text{intention}(O)A}(t))))
+ (1-\beta_{\text{intention}(O)A}) q_{\text{intention}(O)A}(t) \right)
+ (1 - \eta_{\text{intention}(O)A}) q_{\text{intention}(O)A}(t) - q_{\text{intention}(O)A}(t) \right] \cdot \Delta t
\]

### 6.5 Some Example Simulation Results for a Fictional Case Study

In this section, some example results of a small fictional case study will be presented. The goal of the case study was to investigate if the computational model can simulate the interplay of emotions, intentions and beliefs, as described in neuroscientific, social and psychological literature. The computational model was implemented in Matlab in the context of an evacuation scenario (see Appendix A for the complete Matlab specification). The example scenario is expressed as follows: at the end of a working day in an office, the fire alarm goes off and all the persons that are in the building need to evacuate immediately. At the time of the alarm, 3 teams of each 3 people are present on different floors, as can be seen in Figure 6.2. Persons can communicate with each other when they are on the same floor, or they can communicate to each other through their personal device, which is equipped with a tool for sharing emergency information over a short distance. Communication through such personal devices can only occur in case the distance is 3 floors or less. The building has 4 emergency exits, three at the ground floor and one at the 5th floor via a skyway to another building. If an exit is accessible, the information is rated as ‘positive’ information in the model, if not accessible then the information is rated ‘not positive’. In the formalization, this leads to the following information state characteristics: \( p_{\text{ExitX}} = 1 \) for accessible exits and \( p_{\text{ExitX}} = 0 \) for blocked exits. The relevance of this information for survival is always 1, i.e. \( r_{\text{ExitX}} = 1 \).
Fig. 6.2. The location of 3 teams in a building of 6 floors with 4 exits

An example scenario
In the example scenario, the three persons located at the top floor know that exit 4 is available (i.e. they have a belief of 1 in information $p_{\text{Exit4}} = 1$), whereas the three persons on the middle floor do not have any strong beliefs about any of the emergency exits. The three at the first floor know the situation of the exits 1 and 2 at the first floor, thus they have beliefs of strength 1 concerning those exits. In this case, the first exit is blocked and the second is accessible, therefore $p_{\text{Exit1}} = 0$ and $p_{\text{Exit2}} = 1$. They do not know anything about exit 3, therefore a belief of strength 0 is present concerning exit 3. Besides these values, all other values are set to 0.5 with respect to the beliefs to indicate that they know the exits are there but do not know specifically whether the exit is accessible or not. Moreover, the intentions of all agents are initially set to 0 (i.e. they start with not specific intention to leave the building via any of the exits) and the emotions to 0, 1, 0, and 1 for exit 1, 2, 3, and 4 respectively (since exit 1 and exit 3 represent negative information, the emotion for that option is not positive). Finally, for the emotion of fear the agents at the first floor have no fear, at the middle floor they have maximum fear, and at the top floor medium fear is present. Furthermore, the initial belief about the situation itself is 0.5. Regarding all the parameter settings as described before: each agent has the same initial set of parameters, and these can be found in the Matlab specification as shown in appendix A.
Figure 6.3 shows the change of the values of the beliefs, intentions, and emotions. The top four rows represent the values related to the four exits. Here, the values for all agents during the simulation runs are shown. The y-axis of the graphs represents all 9 persons, who have values for certain variables, stated on the z-axis. The values develop over time, which is represented by the x-axis. At the bottom row of the figure, diagrams with the amount of fear and the judgment of the entire situation are shown. It can be seen that fear spreads quickly, resulting in a very negative judgment of the situation by all agents. For exit 1 the belief about the exit being an option for evacuation eventually stabilizes at a relatively low value due to the fact that no human has a good feeling for that option (although in the beginning the emotions are slightly pulled upwards as well as the intention, due to the very strong belief of the three agents at the first floor). For exits 2 and 4 a very strong belief occurs rapidly for all agents as well as a very strong intention and the positive emotions also remain high. Finally, for exit 3 the agents at the first floor get a slightly stronger belief, intention, and emotion due to the fact that the other agents have a belief with value 0.5 about the exit. Eventually however, the values return to a rather low value again due to the fact that the others have
lowered their value again. Without the ability to communicate with each other using personal devices, the beliefs, intentions, and emotions would not have been influenced by those on the other floors.

More systematic variations
The context of this case study was used to explore whether under a variety of parameter settings patterns emerge as expected.

The effect of information on fear
A first prediction about the interplay of emotions, intentions and beliefs, according to the computational model is that from formula (8), it is expected that if a person experiences a situation as dangerous, then this person’s fear level should increase. Simulations where the persons believed that the situation is dangerous were compared with simulations where they believed that that situation was not dangerous. The result of these simulations were that if persons believe that the situation is not dangerous \( (p_{\text{belief}(i)A} = 1) \), then \( q_{\text{fear}(i)A}(t) \) goes to 0, meaning that the persons will experience no fear. If the persons believe that the situation is dangerous \( (p_{\text{belief}(i)A} = 0) \), then \( q_{\text{fear}(i)A}(t) \) increases to 1, meaning that the persons will increase their experience of fear, when they consider the situation as dangerous. This result corresponds with our expectation.

The effect of emotion on beliefs
According to formulas (5), (6), and (7) the level of fear that a person is experiencing, can have an effect on the way a person processes information. More precisely: it is expected that when \( q_{\text{fear}(i)A}(t) \) is above threshold \( \tau \), then the emotion fear should have an effect on the way persons process information. Multiple simulations were run to test this. In the simulations, the threshold \( \tau \) was set to 0.5 and the initial value of \( q_{\text{fear}(i)A}(t) \) is below or above threshold \( \tau \), for example, 0.1 or 0.7. Whenever \( q_{\text{fear}(i)A}(t) \) is above the threshold \( \tau \) (either from the start, or at a later time point), \( \delta_{\text{belief}(X)A}(t) \), \( \eta_{\text{belief}(X)A}(t) \) and \( \beta_{\text{belief}(X)A}(t) \) start to change indeed. Here results will be briefly presented where \( \zeta \) was 1.

- The openness \( \delta_{\text{belief}(X)A}(t) \) becomes 1 or stays 1, this is according to the model, because when \( \zeta = 1 \) and \( r_{\text{belief}(i)A} = 1 \) (the information is relevant for survival), \( \delta_{\text{belief}(X)A}(t) \) should increase.
- The bias factor \( \beta_{\text{belief}(X)A}(t) \) increases for the situation, exit 1 and 3 (which are not accessible), but decreases for exit 2 and 4 (which are accessible). This is what was expected, because the higher \( p_{\text{belief}(i)A} \) is (meaning the more ‘positive’ information is), the lower \( \beta_{\text{belief}(X)A}(t) \) should become (meaning information will be spread weaker by this person), the lower \( p_{\text{belief}(i)A} \) is, the
higher $p_{\text{belief}(X)A}(t)$ should become (meaning strengthening the spread of negative information).

- The amplification extent $\eta_{\text{belief}(X)A}(t)$ increases differently for the situation, where exit 1 and 3 are not accessible. For this situation it goes towards 1 and it increases more, the further the agents are away from the exit. This is according to expectation, because $\eta_{\text{belief}(X)A}(t)$ should only increase if $p_{\text{belief}(i)A}$ = low and $r_{\text{belief}(i)A}$ = high, in these instances, $p_{\text{belief}(i)A} = 0$ and $r_{\text{belief}(i)A} = 1$. For exit 2 and 4, $p_{\text{belief}(j)A} = 1$ and $r_{\text{belief}(j)A} = 1$. In that case $\eta_{\text{belief}(X)A}(t)$ should not increase, and that is what is happening correctly in this evacuation scenario.

The effects of a combination of beliefs and emotions

In the simulations it was found that the combination of emotions and beliefs decreases the level of $q_{\text{emotion}(X)A}(t)$ more than they do separately. This effect was expected from formula (1) for $q_{\text{emotion}(X)A}(t)$. For example, here one can see that in this situation the combination of emotions and beliefs makes $q_{\text{emotion}(X)A}(t)$ increase more, than when beliefs are not combined with emotions.

A Real World Case Study: the May 4 Incident

The computational model mentioned above was applied to the May 4 incident in Amsterdam (The Netherlands). The incident took place in the evening of May 4th 2010, when approximately 20,000 people gathered on Dam Square in Amsterdam for the National Remembrance of the dead. What follows is a short description of the events.

At 20:00h everyone in the Netherlands, including the crowd on Dam Square, was silent for 2 minutes to remember the dead. Fences and officials compartmented the 20,000 people on Dam Square. At 20:01 a man in the crowd on Dam Square disturbed the silence by screaming loudly. People standing directly near him could see that this man looked a bit ‘crazy’ or ‘lost’, and they did not move. Those not within a few meters of the screaming source, started to panic and ran away from the man that screamed. The panic spread through the people that were running away who infected each other with their emotions and intentions to flee. This panic was fuelled by a loud ‘BANG’ that was heard about 3 seconds after the man started screaming. Queen Beatrix and other royal members present were escorted to a safe location nearby. In total, 64 persons got injured: they got broken bones and scrapes by being pushed, or got run over by the crowd. The police exported the screaming man and got control over the situation within 2 minutes. After 2½ minutes, the master of ceremony announced to the crowd that a person had become ill and had received care. He asked everybody to take his or her initial place again, and to continue the ceremony. After this, the ceremony
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continued. Eyewitness reports were collected on site. Below, parts of their transcripts are freely translated in English:

**Question: describe what happened in your own words.**

**Eyewitness 1:** “[….] The moment people in front of me started to run, I panicked. I could not see why these people ran away. It seemed they were running away from something. I immediately thought back to what happened the year before in Apeldoorn [the witness refers to the failed attack on the Royal Family the year before, when someone drove his car into the crowd towards the Royal Family and killed 8 people]. After the yelling, I heard a lot of noise, which later turned out to be fences that fell down… […] The few seconds when people started to run away after the scream, I found the most scary.”

**Eyewitness 2:** “[…] The moment the man started screaming, I ‘choked’ of fear: I thought that someone wanted to disrupt the ceremony with an attack and I was afraid that we, including our little daughter, would be run over.”

**Eyewitness 3:** “[…] “My panic was growing when people behind us ran into the fences in ‘blind panic’. The moment I saw fences falling down en people tripping over them was the peak of my panic. After that, I felt shocked and surprised, because people shouted ‘Not again?!’. We helped people get back up on their feet and after that I fell into the arms of my friends and tried to relax. Because of the adrenaline, I couldn’t manage easily. I had a bad feeling about the applause after the message of the master of ceremony: the message that somebody became ill and was taken care off, was clearly a lie and the applause was out of place.”

**Question: how did you interpret the scream?**

**Eyewitness 1:** “Like an emergency call or yell of somebody with the wrong intentions.”

**Eyewitness 2:** “As a suicide terrorist who braces himself before he will act.”

**Eyewitness 3:** “As a tortured soul that lost somebody and could only express this by screaming.”

**Question: did you get information about the situation from people around you?**

**Eyewitness 1:** “No.”

**Eyewitness 2:** “No, only that everybody was scared. “

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4 A short movie with images from the live broadcast on Dutch National Television, can be found at: http://www.youtube.com/watch?v=0cEQp8OQi2Y. This shows how, within two minutes, the crowd starts to panic and move.
Eyewitness 3: “People, police and veterans were running everywhere. All attention was focused on the wounded and on recovering the peace. No information came to us.”

The live broadcast of the National Remembrance on Dutch National Television has been acquired in HD-quality. In this video, one can see the crowd on Dam Square flee from the perspective shown in Fig. 6.4. The video includes the cuts and editing that were done during the live broadcast, because the un-edited video material of all cameras that were filming that day was not saved.

![Fig. 6.4. Still image of the people on Dam Square starting to flee. The circle on the right bottom indicates the location of the yelling person](image)

From the total broadcast, a shorter 3-minute movie was made, starting the moment when the crowd was silent and the person started to scream loudly. In this 3-minute movie there are two time slots that were further processed (11-17 seconds and 20-27 seconds), because (i) they showed the clear camera angle like the one that can be seen in Fig. 6.4, and (ii) the direction and speed of the movements of people could be clearly analysed. They were analysed as follows. The movie was cut into still images, to detect the location of people by hand. Ten still images per second were chosen in order to be able to detect the movements of running people frame by frame. By keeping track

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5 Permission granted for educational and research purposes by The Netherlands Institute for Sound and Vision.
of the coordinates of mouse-clicks on the locations of people in the crowd while they were moving, their trace of movement could be detected.

A total of 130 frames were analysed by hand. Not all people could be analysed, both because of the quantity, and the impossibility to trace every ‘dot’ (person) over multiple still images. Persons in different positions of the crowd with simultaneous movements to the people around them were chosen, such that these target subjects were able to represent multiple people around them. In total 35 persons were traced. See Figure 6.5, for an example of 5 of the persons that were traced. The red dot represents the screaming man. The five blue lines represent the 5 persons that were traced. The arrows indicate in which direction the persons ran away. The x- and y-axis contain the coordinates.

![Fig. 6.5. Escape directions of 5 persons that were traced by hand](image)

The density of the crowd around a target subject was also acquired, which could be used to build a representative large-scale simulation consisting of ten thousands of agents. Since the exact number of persons surrounding a target could not be distinguished in the video, 3 distinctions in density were made: high, medium and low. The size of the circle around the target subject, in which density was measured, is shown on the right in Figure 6.4.

The next step was to correct for the angle the camera makes with the floor by recalculating the coordinates into coordinates that would fit into a bird’s-eye view on the Dam Square, perpendicular to the floor. People’s distance in meters from corners of the buildings were translated to the position in pixels on a 600x800 map of the area, using offsets and scaling. Specifically, the following formulae are used to translate movements in pixels to movements in meters:

\[
\begin{align*}
x_{\text{meter}} &= x_{\text{pixel}} / 22 \\
y_{\text{meter}} &= y_{\text{pixel}} / 8
\end{align*}
\]
This was then transformed to the map using the following formulae:

\[
x_{\text{map}} = (x_{\text{meter}} \times 5.15) + 136
\]
\[
y_{\text{map}} = (y_{\text{meter}} \times 5.15) - 167
\]

The bird’s eye view perspective used in the computational model can be seen in Fig. 6.6. The resulting figure was represented in the simulation in Matlab.

![Fig. 6.6. 600 x 800 pixel image of the Dam Square](image)

Locations of certain obstacles, like buildings and fences, were also transformed into the bird’s-eye view.

6.6 Extending and Specialising AScribe for the May 4 Case

To tailor the model AScribe towards the domain introduced in Section 6.6, a number of steps were taken.
Case specific states
First of all, the relevant states for the agents have been distinguished. In this case, the emotion, belief and intention states relate to the options for each agent. A total of 9 options are available including ‘remain standing’, and moving in any wind direction (N, NE, E, SE, S, SW, W, NW). Besides these, there is an additional belief about the current situation. This expresses how positive a person judges the current situation (0 a negative judgment, and 1 a positive judgment). Finally, the emotions for each option and the emotion fear is represented.

Channel strength
In the scenario described above, the channel strengths between the various agents are dependent on the physical location of the agents. If other agents are close, the channel strength is high, whereas it is low or 0 in case agents are far apart. Therefore, a threshold function was used expressing within which reach agents still influence each other in a significant manner:

\[ \alpha_{BA}(t) = 1 - \frac{1}{1+e^{\sigma(distance_{BA}(t) - \tau distance)}} \]

Here \( \sigma \) and \( \tau distance \) are global parameters and \( distance_{BA} \) is the Euclidean distance between the positions \((x_A(t), y_A(t))\) and \((x_B(t), y_B(t))\) of A and B at \( t \).

Movement
The movement of the agents directly depends upon their intentions. Recall that the strength of the intention is determined by the intentions of others (see section 6.3), and the agent’s own personality characteristics and mental states, such as beliefs and emotions (see section 6.4). The highest feasible intention is selected (in cases where certain movements are obstructed, the next highest intention is selected). For each of the selected options \( O \), the movement \( x_{movement(O)} \) on the x-axis and \( y_{movement(O)} \) on the y-axis is specified; e.g., the option for going south means -1 step on the y-axis and none on the x-axis: \( x_{movement(O)} = 0 \) and \( y_{movement(O)} = -1 \). The actual point to which the agent will move is then calculated by taking the previous point and adding the movement of the agent during a certain period to that. The movement of the agent depends upon the strength of the intention for the selected option and the maximum speed with which the agent can move. If the intention is maximal (i.e., 1) the agent will move with the maximum speed. In case the intention is minimal (i.e., 0) the agent will not move. The model that establishes this behaviour is as follows:

\[
\begin{align*}
x_A(t+\Delta t) &= x_A(t) + max_{speed} A \cdot q_{intention(O), A}(t) \cdot x_{movement(O)} \cdot \Delta t \\
y_A(t+\Delta t) &= y_A(t) + max_{speed} A \cdot q_{intention(O), A}(t) \cdot y_{movement(O)} \cdot \Delta t
\end{align*}
\]
Here the maximum speeds \( \text{max\_speed}_A \) are agent-specific parameters.

### 6.7 The Parameter Tuning Method Used

As explained above, the computational model contains a large number of parameters; these parameters address various aspects of the agents involved, including their personality characteristics (e.g., expressiveness, openness, and tendency to absorb or amplify mental states), physical properties (e.g., minimum and maximum speed, and limit of their sight), and characteristics of their mutual interactions (e.g., channel strength between sender and receiver). The accuracy of the model (i.e., its ability to reproduce the real world data as closely as possible) heavily depends on the settings of these parameters. Therefore, parameter estimation techniques [31] have been applied to learn the optimal values for the parameters involved.

In order to determine what is ‘optimal’, first an error measure needs to be defined. The main goal is to reproduce the movements of the people involved in the scenario; thus it was decided to take the average (Euclidean) distance (over all agents and time points) between the actual and simulated location:

\[
\varepsilon = \sum_{\text{agents } a} \sum_{\text{timepoints } t} \frac{\sqrt{(x(a,t,\text{sim})-x(a,t,\text{data}))^2+(y(a,t,\text{sim})-y(a,t,\text{data}))^2}}{\#\text{agents} \times \#\text{timepoints}}
\]

Here, \( x(a, t, \text{sim}) \) is the x-coordinate of agent \( a \) at time point \( t \) in the simulation, and \( x(a, t, \text{data}) \) the same in the real data (similarly the y-coordinates). Both are in meters.

Next, the relevant parameters were tuned to reduce this error. To this end, the approach described in detail in Section 6.3 and 6.4 of [2] was used. This approach makes use of the notion of sensitivity of variables for certain parameter changes. Roughly spoken, for a given set of parameter settings, the idea is to make small changes in one of the parameters involved, and to observe how such a change influences the change of the variable of interest (in this case the error). Here, ‘observing’ means running the simulation twice, i.e., once with the original parameter settings, and once with the same settings were one parameter has slightly changed. Formally, the sensitivity \( S_{X,P} \) of changes \( \Delta X \) in a variable \( X \) to changes \( \Delta P \) in a parameter \( P \) is defined as follows (note that this sensitivity is in fact the partial derivative \( \partial X / \partial P \)): \( S_{X,P} = \Delta X / \Delta P \).

Based on this notion of sensitivity, the adaptation process as a whole, is an iterative process, which roughly consists of: 1) calculating sensitivities for all parameters under consideration, and 2) using these sensitivities to calculate new values for all parameters. This second step is done by changing each
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parameter with a certain amount \( \Delta P \), which is determined as follows: \( \Delta P = -\lambda \Delta X / S_{X,P} \). Here, \( \Delta X \) is the deviation found between actual and simulated value of variable \( X \), and \( \lambda \) is a speed factor. Note that, since in the current case \( X \) represents the error, the ‘actual value’ of \( X \) is of course 0, so \( \Delta X \) simply equals \( \varepsilon \) in the simulation.

6.8 Results
This section presents the results of specialising and tuning the agent-based model with 35 agents, to the real world data of the May 4 incident. The results are presented for the first part of the data (i.e., seconds 11-17 of the 3-minute movie). To assess the performance of the model, it was compared with three other models, which are introduced in Section 6.8.1. Next, Section 6.8.2 explains which parameters of those models were tuned, and which parameter settings were found. Section 6.8.3 discusses the results of running the models for the optimal parameter settings found; in particular, for each model the increase of the error over time (of the simulation) is shown. Section 6.8.4 discusses the statistical significance of the results, and Section 6.8.5 illustrates the behaviour of the simulation based on the optimal models found.

6.8.1 Models used for Comparison
To assess the performance of ASCRIBE, it was compared to three other models. First, one baseline model was developed in which the agents do not move at all. Second, the model was compared to an implementation of the model by Helbing and colleagues [17], which is currently one of the most influential models in the area of crowd simulation. This model has been specifically designed for simulating dynamical features of escape panic, and is essentially a specific variant of a social force model for pedestrian dynamics which Helbing and Molnar introduced in 1995 [35]. It has been modelled following the framework of self-driven many particle systems and is based on a general force model. The model assumes that each agent likes to move in a certain direction with a certain desired velocity. In addition however, the agent is influenced by certain interaction forces: it wants to keep a certain distance from other agents and walls. The model is expressed by means of a number of equations (cf. [17]), and a very brief overview of the main equations in the model is presented here. For a complete overview of the model, see [17]. In the first equation the change in the velocity of the agent is given as follows:

\[
m_t \frac{dv_i}{dt} = m_t \frac{v^0(t)e^0(t) - v_i(t)}{\tau_i} + \sum_{j(*i)} f_{ij} + \sum_w f_{iwv}
\]
This expresses that the velocity of the agent changes based upon the desired velocity \(v_i^d(t)\), the desired direction \(e_i^0(t)\), and the current velocity. Note that in the implementation of the model, a more sophisticated variant of the desired direction has been used (cf. [35]) in which a complete set of points to be visited can be expressed, and the desired direction depends on the closest of these points given the current position. The forces that occur due to other agents and walls are added to the equation as well. In the equation, the parameter \(m_i\) represents the mass of the agent, whereas \(\tau_i\) expresses the so-called characteristic time. In order to calculate the forces from other agents and walls, two equations are used. The first of these equations concerns the calculation of the force between an agent \(i\) and \(j\):

\[
f_{ij} = \left\{ A_i \exp\left(\frac{(r_{ij} - d_{ij})}{B_i}\right) + k g(r_{ij} - d_{ij})\right\} n_{ij} + \kappa g(r_{ij} - d_{ij}) \Delta v_{ij}^t \tau_{ij}
\]

The equation indicates that the force between two agents is dependent upon a number of factors. The first part of the equation expresses the body force between the agents, where \(A_i, B_i\), and \(k\) are constants. Furthermore, \(d_{ij}\) represents the distance between the two agents, \(n_{ij}\) is the normalized vector pointing from agent \(j\) to agent \(i\), and \(r_{ij}\) is the sum of the change of positions of agent \(i\) and \(j\). \(g(r_{ij} - d_{ij})\) evaluates to zero in case the pedestrians do not touch each other (i.e. \(d_{ij} > r_{ij}\)) and otherwise to \(r_{ij} - d_{ij}\). The second part of the equation \(\kappa g(r_{ij} - d_{ij}) \Delta v_{ij}^t \tau_{ij}\) represents the so-called sliding friction in case the pedestrians come close to each other. Here, \(\Delta v_{ij}^t\) is the tangential velocity difference, and \(\tau_{ij}\) the tangential direction.

The second equation concerns the interaction with walls and is quite similar to the equation used for the interaction with other agents:

\[
f_{iW} = \left\{ A_i \exp\left(\frac{(r_i - d_{iW})}{B_i}\right) + k g(r_i - d_{iW})\right\} n_{iW} - \kappa g(r_i - d_{iW}) (v_i \cdot t_{iW}) t_{iW}
\]

In this case, \(d_{iW}\) is the distance between the agent and the wall, and \(n_{iW}\) is the direction perpendicular to the wall. Furthermore, \(t_{iW}\) is the direction tangential to the wall.

Finally, next to the no motion model and the Helbing et al. model, a variant of ASCRIBE was developed in which all agents also make individual decisions, but do not influence each other (i.e., no contagion takes place). This was done to assess whether the idea and implementation of contagion of mental states is useful at all.

This resulted in three different models (in addition to our own model ASCRIBE with contagion of mental states), to which we refer below as baseline, Helbing, and without contagion, respectively. To enable a fair comparison,
parameter tuning was applied for all models (except for the baseline model, since it did not contain any parameters to tune) in order to find optimal settings, as explained in the next section.

6.8.2 Parameter Settings
The number of parameters to tune for the full model ASCRIBE is large; therefore, before starting the tuning process for this model, the settings for a large majority of the parameters were fixed at default values (see Table 6.4). For example, parameters with a relatively small sensitivity were left out of consideration for the tuning process (cf. [2]). For these parameters, reasonable default settings were chosen by hand (based on experimentation). The values of the remaining parameters (among others, the maximum speed for each individual agent, the minimum distance within which agents influence each other, and the initial values of one of the beliefs, see Table 6.4) were initialised by hand, but were then adapted using the parameter tuning approach described in the previous section.

The speed factor $\lambda$ of this tuning process was set to 0.1. The initial locations of the agents involved were taken equal to the locations in the real world data. An overview of all optimal settings found for the global parameters and the initial variables involved in the model is shown in Table 6.4.

Here, the settings shown in the first two columns were set by hand, and the settings shown in the last two columns were found after tuning. Note that all settings (except those for maximum speed) were used globally for all agents. For the model without contagion, the tuned parameters were the same as for the full model with contagion. For the Helbing model, the parameters that were tuned were also the desired speed for all individual agents ($v^*(t)$) as well as the global parameters characteristic time $\tau_i$ and the difference between the points to be visited (representing the path the agent want to follow). Moreover, for the parameters $A$, $B$, $k$ and $\kappa$, the settings as prescribed in their article [17] were taken and as desired direction $(e^*(t))$, the direction precisely opposite to the location of the shouting man was selected, and points were generated which form a path away from this location (thereby setting the desired direction to the closest point as explained before). The distance between these points depended on the setting of the parameter. For all models, the tuning was continued until the improvements made per iteration were smaller than 0.1%.
Table 6.4. Optimal parameter settings found

<table>
<thead>
<tr>
<th>Global parameters (not tuned)</th>
<th>Initial variable settings (not tuned)</th>
<th>Global parameters (tuned)</th>
<th>Initial variables (tuned)</th>
</tr>
</thead>
<tbody>
<tr>
<td>#agents</td>
<td>35</td>
<td>εintention</td>
<td>0.5</td>
</tr>
<tr>
<td>max_x</td>
<td>600</td>
<td>δintention</td>
<td>0.5</td>
</tr>
<tr>
<td>max_y</td>
<td>800</td>
<td>ηintention</td>
<td>0.5</td>
</tr>
<tr>
<td>Δt</td>
<td>0.5</td>
<td>βintention</td>
<td>0.5</td>
</tr>
<tr>
<td>µbelief</td>
<td>0.5</td>
<td>εbelief</td>
<td>0.5</td>
</tr>
<tr>
<td>µbelief</td>
<td>0.5</td>
<td>δbelief</td>
<td>0.5</td>
</tr>
<tr>
<td>µbelief</td>
<td>0.5</td>
<td>ηbelief</td>
<td>0.5</td>
</tr>
<tr>
<td>σ</td>
<td>100</td>
<td>εemotion</td>
<td>0.5</td>
</tr>
<tr>
<td>σ</td>
<td>100</td>
<td>δemotion</td>
<td>0.5</td>
</tr>
<tr>
<td>σ</td>
<td>100</td>
<td>ηemotion</td>
<td>0.5</td>
</tr>
<tr>
<td>σ</td>
<td>100</td>
<td>ω</td>
<td>0.5</td>
</tr>
</tbody>
</table>

6.8.3 Increase of Error over Time

Fig. 6.7 shows for each of the four variants how the average error (over all agents) increases during the simulation. Note that the error is expressed in meters. At the first time point, the error is 0 (all agents start at their actual position), but over time the error increases very quickly in the baseline case, so that the overall average error becomes quite large (0.87). The overall error found for the tuned model without contagion is much lower (0.66, i.e., an improvement of 24%), and is even lower for the tuned model with contagion (0.54, i.e., an improvement of 38%). This finding provides evidence for the conclusion that incorporating the contagion makes the model more accurate, even when it is based on default settings for the parameters. Note that in the current scenario, the agents’ movements involve relatively small steps, compared to the size of the grid; in case the steps would have been larger, the difference in performance between the three models would be expected to have been bigger as well.

As for the Helbing model, the overall average error of this model was found to be 0.59. As can be observed from Fig. 6.7, this model performs better than the model without contagion, but worse than the model with contagion (at least, in this particular scenario). One of the main reasons for this is that the model with contagion seems to be better able to deal with the fact that some
agents only start moving half way the scenario. This phenomenon, which is also well visible in the video of the event, is caused by the fact that the crowd is separated by fences (see also Fig. 6.4), and especially the people that are located on the left hand side of the area wait a couple of seconds before they start moving, whereas other people start moving right after the scream. In the model with contagion, this phenomenon can be reproduced quite accurately by means of the contagion mechanism: the agents at the left hand side of the area initially have a low level of fear (since they are not directly affected by the screaming man), but only when they observe other agents panicking and trying to escape, they are influenced by them and attempt to get away as well. Since the Helbing model does not include an explicit mechanism for contagion of mental states, it has more difficulties in reproducing this particular effect (because in this model, the speed by which the agents move is more stable - although not completely constant - over time). Therefore, for the Helbing model, the parameter tuning resulted in an optimal situation where some agents on the left hand side hardly move at all. This is reflected by the fact that the error for this model (compared to the model with contagion) only increases in the last 8 time steps.

![Graph showing error development over time for three models](image_url)

**Fig. 6.7.** Development of error over the simulation for three variants of the model.

When comparing the Helbing model with the model without emotion, one can observe that, although the errors of both models are time point 45 are comparable, the Helbing model performs slightly better when taking the overall average error over all time points. This can in part be explained by the fact that the Helbing model has more freedom when it comes to selecting the direction in which the agents move. In our model (both with and without contagion), selection of actions has been implemented in such a way that the
agents can only pick one out of 8 wind directions (see Section 6.7), whereas the Helbing model uses a continuous scale for this. We speculate that the performance of our model (both with and without contagion) may be further improved by changing this discrete mechanism for action selection into a continuous mechanism.

![Graphs showing standard error at each time point for four models.](image)

**Fig. 6.8.** Standard error at each time point for the four models.

In order to provide some more insight in the variance of the error over the 35 agents, additional graphs have been generated which show the standard error.
of the mean ($\sigma/\sqrt{n}$, i.e., the standard deviation divided by the square root of the number of agents) at each time point for all models; see Fig. 6.8. These graphs show that the standard error is relatively small, which implies that errors are fairly distributed over the 35 agents, although there are some outliers (between 1 and 2.5 standard deviations), see next section. They also show that the standard error is largest for the baseline model, and smallest for the model with contagion.

6.8.4 Statistical Analysis

A two-way within-subjects analysis of variance was conducted to evaluate the effect of the type of computational crowd behaviour model on deviation from the walking direction in the real world scenario. The analysis has been conducted for all time points of the simulation, for 35 agents. The dependent variable was the deviation from the walking direction in the real world scenario data named ‘error’, which was measured in meters. The within-subjects factors were type of crowd behaviour models, with 4 levels (Baseline, Helbing, ASCRIBE without contagion, ASCRIBE with contagion) and time with 47 levels (47 time steps of the simulations). The main effects and interactions were tested using the univariate Huynh-Feldt analysis that corrects for non-sphericity. The Model main effect was significant, $F(1.4, 48.2)=5.7, p<0.012$, the Time main effect was significant, $F(1.3, 45.6)=26.1, p=0.012$, and the ModelxTime interaction effect was significant, $F(2.5, 87.5)=6.7, p=0.001$. To further inspect which models differ significantly from each other, each combination of 2 models was tested with post hoc pairwise comparisons with LSD adjustment for significance on the p<0.05 level. Significant differences were found between Baseline and Helbing, p<0.05, Baseline and ASCRIBE with contagion, p<0.05, ASCRIBE without contagion and ASCRIBE with contagion, p<0.001, and a trend was found between Baseline and ASCRIBE without contagion, p=0.074. No significant difference was found between ASCRIBE with contagion and Helbing, p=0.322 and between Helbing and ASCRIBE without contagion, p=0.171.
Fig. 6.9 Individual agent’s error per model.
These results seem to point in the direction that all models differ significantly, except Helbing from ASCRIBE with contagion and Helbing from ASCRIBE without contagion. Indeed, in Figure 6.7, Helbing and ASCRIBE without contagion do seem to behave alike, but Helbing and ASCRIBE with contagion seem to differ substantiously. We feel that when there would be more timesteps available in the real world data, the Helbing model would differ significantly from ASCRIBE with contagion, and perhaps even from ASCRIBE without contagion. Furthermore, when investigating the data further, two outliers can be found that differ between 1 and 2 standard deviations of the other 33 agents. (In Figure 6.9 it can be seen that each model always has minimum 1 or 2 agents that behave very differently from the rest). When these 2 outliers are removed, all previously found significant differences stay significant (on the p<0.01 level), the difference between Helbing and ASCRIBE without contagion is still not significant, p = 0.38, and a trend becomes visible between Helbing and ASCRIBE with contagion, p=0.054. These results point into the direction that all models differ significantly from each other in this scenario, except Helbing and ASCRIBE without contagion.

A second research question to be analysed statistically is: do the 4 computational models differ significantly on the second half of the simulation, compared to the first half of the simulation. This research question stems from the fact that in the second half of the simulation the whole mass of people is moving, compared to the first half of the simulation, where only the right half of the mass starts to move. In this way, the data has two distinct time points that can be compared, by summing up all data points per model, per half of the simulation. A two-way within-subjects analysis of variance was conducted to evaluate the effect of type of computational crowd behaviour model on deviation from the walking direction in the real world scenario on two time points: the first and second half of the simulation. See Figure 6.10 for an overview of the summed errors per model, per time step. The within-subjects factors were type of crowd behaviour model with 4 levels (Baseline, Helbing, ASCRIBE without contagion, ASCRIBE with contagion) and time with 2 levels (the summed first half and second half of the simulation). The main effects and interactions were tested using the univariate Huyhn-Feldt analysis that corrects for non-sphericity. The Model main effect was significant, $F(1, 35.3)= 8.9, p=0.005$, the Time main effect was significant, $F(1,34)=77.9$, $p<0.001$, and the ModelxTime interaction effect was significant, $F(1.1, 36.2)=10.5, p=0.002$. To further inspect which models differ significantly from each other, each combination of 2 models was tested with post hoc pairwise comparisons with LSD adjustment for significance on the $p<0.05$ level.

Significant differences were found between all models: Baseline and Helbing,
$p<0.01$, Baseline and ASCRIBE without contagion, $p<0.05$, Baseline and ASCRIBE with contagion, $p<0.001$, Helbing and ASCRIBE without contagion, $p<0.001$, Helbing and ASCRIBE with contagion, $p<0.001$, ASCRIBE without contagion and ASCRIBE with contagion, $p<0.001$.

**Fig. 6.10.** Summed errors for all agents, per model, per half of simulation.

### 6.8.5 Resulting Behaviour of the Simulation

After the tuning process was finished, the optimal settings found for all parameters were used as input for the four simulation models, to generate simulation traces which closely resemble the real world scenario. Using visualisation software (written in Matlab), these simulation traces have been visualised in the form of a 2D animation. A screenshot of the animation of the model with contagion is shown in Fig. 6.11.

Here, the lines represent fences that were used to control the crowd, the large circle represents the monument on the square (see Fig. 6.4 for the actual situation), and the big dots represent corners of other buildings. The plus sign on the right indicates the location of the screaming man. The small dots represent the actual locations of the 35 people in the crowd that were tracked, and the stars represent the locations of the corresponding agents in the simulation. Even at the end of the simulation (see Fig. 6.11), the distances between the real and simulated positions are fairly small for this model.

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*See [http://www.few.vu.nl/~tbosse/may4/](http://www.few.vu.nl/~tbosse/may4/). This URL contains two animations: one in which only the result of the model with contagion is shown, and one in which the results of all four models are shown together.*
6.9 Comparison to an epidemiological-based contagion model

As described in detail in Section 6.3 and 6.4, the model AScribe presented in this chapter is an interaction-based model that draws from social contagion theories of emotion and other mental states, such as beliefs and intentions. The final model resembles the dynamics properties as they are found in thermodynamic systems, for example heat diffusion by the interaction of bodies and radiation. A different approach to modelling contagion is used by epidemiological models, which are traditionally well suited to describe phenomena such as the disease spread (e.g., [36]) or innovation diffusion [37],
but are also heavily applied to different types of social contagion (e.g., [38]). One example of an epidemiological model that has been applied to social contagion is the Durupinar model [39]. This model uses probabilistic thresholds to determine the likelihood of emotion ‘infections’ between people in social interactions.

In recent work, Tsai et al. have compared ASCRIBE and the Durupinar model in an evacuation simulation where both models were tested on their ability to reproduce the dynamics that occurred in an existing crowd panic scene [40]. The simulation was run in ESCAPES [33], which is a multiagent evacuation simulation tool that features different agent types and emotional, informational and behavioral interactions. For this comparison, an earlier and simpler version of ASCRIBE (as presented in [41]), was used. This model does not include the dynamics between emotions, intentions and beliefs, but focuses only on the spread of emotions. Tsai et al. did however expand the simpler version with a proximity effect that is similar to the one used in the extended model ASCRIBE described in this chapter (see Section 6.7).

First, a simulation was run that included 100 pedestrians, who experience a fearful event and as a result are trying to find an exit in a large hallway. The results show that ASCRIBE was able to produce more realistic dynamics than the Durupinar model. In ASCRIBE, the proximity effect ensured that agents could only be affected by others in their proximity, whereas in the Durupinar model, contagion was able to spread through the entire population immediately. See [40] for a detailed discussion of these results.

Second, ASCRIBE was compared to both the Durupinar model and the ESCAPES model, as a baseline comparison. The ESCAPES model uses a basic model of emotion contagion wherein agents inherit the highest fear level of neighbouring agents. The simulations were based on two real scenes: the Amsterdam 4 May scene as described in Section 6.6, and recent protests in Greece, where officers fired tear gas in the middle of a small crowd. In both scenarios, ASCRIBE performs equal and mostly superior to the other models, outperforming the Durupinar model with 14% less error per agent per frame in the Amsterdam scenario, and 12% less error per agent per frame in the Greece scenario. See Table 6.5 en 6.6 (adapted from [40]) for the average errors in pixels (compared to the original video’s). Each model shows errors for all agents (‘overall’) and agents near to the catalyzing event (‘near’). The models were run in different parameter settings: as given, with implementations of ‘decay’ turned on/off, with emotional level impacting speed ignored, and with proximity effects turned off. For a discussion on the scenarios, settings and results please refer to [40].
Table 6.5. Average error (in pixels) in the Amsterdam simulation (table adapted from Tsai et al. [40])

<table>
<thead>
<tr>
<th>Model</th>
<th>Overall</th>
<th>Near</th>
<th>Model</th>
<th>Overall</th>
<th>Near</th>
</tr>
</thead>
<tbody>
<tr>
<td>None</td>
<td>0.375</td>
<td>0.699</td>
<td>ESCAPES</td>
<td>0.375</td>
<td>0.698</td>
</tr>
<tr>
<td>ASCRIBE</td>
<td>0.362</td>
<td>0.663</td>
<td>Durupinar</td>
<td>0.383</td>
<td>0.758</td>
</tr>
</tbody>
</table>

Table 6.6. Average error (in pixels) in the Greece simulation (table adapted from Tsai et al. [40])

<table>
<thead>
<tr>
<th>Model</th>
<th>Error</th>
<th>Model</th>
<th>Error</th>
<th>Variation</th>
<th>Overall</th>
<th>Near</th>
</tr>
</thead>
<tbody>
<tr>
<td>None</td>
<td>1.635</td>
<td>Base</td>
<td>1.478</td>
<td>Base</td>
<td>1.478</td>
<td></td>
</tr>
<tr>
<td>ESCAPES</td>
<td>1.478</td>
<td>Decay</td>
<td>1.474</td>
<td>Decay</td>
<td>1.466</td>
<td></td>
</tr>
<tr>
<td>ASCRIBE</td>
<td>1.478</td>
<td>No Speed</td>
<td>1.567</td>
<td>No Speed</td>
<td>1.653</td>
<td></td>
</tr>
<tr>
<td>Durupinar</td>
<td>1.656</td>
<td>No Prox</td>
<td>1.658</td>
<td>No Prox</td>
<td>1.660</td>
<td></td>
</tr>
</tbody>
</table>

These results show that the underlying mechanisms used in ASCRIBE with contagion are well suited to model these kind of contagion problems. It seems that in this case the combination of the proximity effect and the mirroring of emotional states yields the most promising results. Future studies will have to show whether the addition of belief and intention dynamics are able to further decrease the error rate.

6.10 Discussion
This chapter has presented the computational model ASCRIBE for collective decision making based on neural mechanisms revealed by recent developments in Social Neuroscience; e.g., [4], [5], [13], [16], [20]. These mechanisms explain how mutual adaptation of individual mental states can be realized by social interaction. They do not only enable intentions to converge to an emerging common decision, but at the same time enable to achieve shared underlying individual beliefs and emotions. Therefore a situation can be achieved in which a common decision that for each individual is considered in agreement with the own beliefs and feelings can be made. More specifically, this model for
collective design making involves on the one hand individual beliefs, emotions and intentions, and on the other hand interaction with others involving mirroring of such mental states; e.g., [20], [29], [32]. As shown in Figure 6.1 and in Table 6.1, the model involves seven types of interactions: three types of mirroring interactions between different persons, and within each person four types of interactions between the individual mental states.

In earlier work presented in [18] a simpler model for decision making was introduced in which only decision options and emotions associated to them, and their mutual interaction play a role, and no fear, nor interactions with beliefs. This model covers only three of the seven types of interaction of the currently presented model. The overlap is mainly in the somatic marking of intentions for decision options. In [19] a model was introduced in which only emotions and information and their mutual interaction play a role, and no decision-making. The equations for the dynamics of $\delta$, $\eta$, and $\beta$ were adopted from this chapter.

Moreover, it was discussed how empirical data has been extracted from available video material and witness reports of the May 4 incident in Amsterdam. Qualitative data about escape panics are rare [17]. Based on these data, it is possible to compare models for crowd behaviour with qualitative data of a real panicking event. In this chapter, ASCRIBE has been adapted to construct a model for behaviour in a crowd when a panic spiral occurs.

Experiments have been performed in which the model was compared to three other models, namely 1) a baseline model where the agents do not move at all, 2) a model by Helbing and colleagues [17], and 3) a variant of the model where parameters related to contagion were set in such a way that there was no contagion at all; in this case the movement of individuals is only determined by their individual state. In the full model ASCRIBE, mutual influencing took place because emotions, beliefs and intentions were spreading to persons nearby. When comparing the simulations of the four models with the most optimal settings for certain parameters, the variant with contagion had the lowest average error rate ($0.54$ instead of $0.59$, $0.66$, and $0.87$ for Helbing, without contagion, and baseline, respectively). Statistical analysis confirmed the significant differences between the models, in particular for the second part of the scenario. Thus, it is shown that the contagion of mental states is an essential element to model the behaviour of crowds in panic situations.

As discussed in Section 6.9, the added value of the contagion of mental states can be exploited well in the chosen scenario, because of some specific characteristics of this scenario. In particular, the fact that part of the crowd stands still during the first part of the scenario, and only starts to move after they observe (and are probably influenced by) the behaviour of others is a phenomenon that is well suited to be simulated by means of contagion.
mechanisms. Based upon our analysis, this is the main reason why ASCRIBE performs better than the other three models (in which these mechanisms are lacking) in this experiment. Note that this does not necessarily mean that it performs better than, e.g., the Helbing model in other scenarios. A more extensive comparison between these two models for various new scenarios would be an interesting direction for follow-up research.

Previous works have presented several models for crowd behaviour. As mentioned above, an influential paper has been written by Helbing and colleagues [17], in which a mathematical model for crowd behaviour in a panic situation is presented, based on physics theories and socio-psychological literature. This model is based on the principle of particle systems, in which forces and collision preventions between particles are important. This approach is often used for simulating crowd behaviour in virtual environments [30, 34]. In [3] the model of [17] is extended by adding individual characteristics to agents, such as the need for help and family membership. In both models, there are no individual emotion, belief and intention states that play a role. In contrast, in [22] an agent has an ‘emotional status’, which determines whether agents walk together (i.e. it influences group formation). The emotional status of an agent can change when to agents meet. An even further elaborated role of emotional and psychological aspects in a crowd behaviour model can be found in [24]. In this model, several psychological aspects influence the decision making of individual agents, for example, motivation, stress, coping, personality and culture. In none of the models presented above, there is contagion of emotional or other mental states between people. Also, no evaluation with real qualitative data has been performed. One of the most developed tools for crowd simulation, which also incorporates mental states, is ESCAPES [33]. This system, which specifically targets evacuation scenarios, has several similarities with the approach shown here. In Section 6.10 results of a previous study are shown that compares ASCRIBE with the ESCAPES model and the epidemiological-based Durupinar model [40]. These results show that the ASCRIBE model is well equipped to model realistic contagion of emotions. Future work will explore the possibilities to incorporate the detailed mechanisms for contagion of mental states presented here into ESCAPES.

Moreover, in the future, further parameter tuning experiments are planned to study the effect of the parameters that were fixed as default values in the current experiments. The aim is to explore whether even more realistic simulations can be achieved by exploiting the details of the model for contagion of emotions, beliefs and intentions in a more differentiated form. This work has, for reasons of simplicity and clarity, focused on homogeneous groups of agents. However, the model accounts for various personality
settings. Further research will examine how persons with different personalities can influence the contagion process.

Acknowledgement
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References
Part III: Integrated Modelling of Social Contagion and Internal Dynamics


Chapter 7- Analysis of Beliefs of Survivors of the 7/7 London Bombings: Application of a Formal Model for Contagion of Mental States

Tibor Bosse, Vikas Chandra, Eve Mitleton-Kelly and C. Natalie van der Wal

Abstract. During emergency scenarios, the large number of possible influences between cognitive and affective states of the individuals involved makes it hard to analyse their (collective) behaviour. To study the behaviour of crowds during emergencies, this chapter proposes a methodology based on formalisation of empirical transcripts and agent-based simulation, and applies this to a case study in the domain of the 7/7 London bombings in 2005. For this domain, first a number of survivor statements have been formalised. Next, an existing agent-based model, which has a basis in Social Neuroscience, has been applied to simulate the scenarios described in the statements. By means of a formal comparison, the simulation model was found capable of closely reproducing the real world scenarios.
7.1 Introduction
During large-scale emergencies such as terrorist attacks, natural disasters, or chemical accidents, the people involved may behave in unexpected manners. For example, some individuals may immediately start to panic and ‘lose control over their actions’, whereas others may emerge as ‘calm leaders’ and start helping other people. Especially in larger crowds, the large number of possible influences of mental states within individuals (e.g., person A has the belief that he will die, and therefore starts panicking) and between individuals (e.g., person B manages to calm down person A) makes it very hard to predict how a certain crowd will behave in a particular situation. Nevertheless, gaining more insight in the dynamics of these processes is very useful, since it enables policy makers to explore possibilities for developing procedures and interventions to minimise the amount of casualties in such emergency scenarios (e.g., implementing emergency exits at appropriate locations in buildings, or endowing patrollers with intelligent devices that recommend escape routes). In line with recent developments [2,13], this chapter proposes to study such dynamics by means of agent-based simulations.

More specifically, to be able to analyse the dynamics of mental states and their intra- and interpersonal interaction in emergency scenarios, the agent-based simulation model ASCRIBE (Agent-based Social Contagion Regarding Intentions Beliefs and Emotions) has been developed [9]. This model has been inspired by several concepts from Social Neuroscience [6,7], among which the concepts of mirror neuron (i.e., a type of neuron that fires not only when an individual performs an action, but also when he/she observes this action performed by someone else [10,11]) and somatic marker (i.e., a feeling induced by a certain decision option considered by an individual, which helps the individual make decisions by biasing that option [1,7]). Based on these concepts, ASCRIBE describes how for different individuals in a crowd, the strength of their beliefs, intentions and emotions may evolve in certain scenarios.

The main goal of the current chapter is to show how the model can be used to analyse the dynamics of individuals’ mental states for a real world incident. To this end, a case study is performed which addresses the analysis of the London bombings on July 7th, 2005. To test the applicability of the model for this case, a research methodology is followed that consists of a number of steps. First, a set of survivor statements which were extracted from the ‘Report of the 7 July Review Committee’ [12], have been formalised using a dedicated ontology. Next, ASCRIBE has been applied to generate a number of simulation runs for fragments of the scenarios described in the survivor statements. And finally, the results of the simulations have been compared
with the formalised survivor statements, both in an informal and in a formal manner (using an automated tool).

The remainder of this chapter is organised as follows: Section 7.2 provides a brief description of the London bombings. Section 7.3 explains how statements of survivors of the attack were obtained and converted to formal notation. Next, Section 7.4 summarises the main mechanisms of the model ASCRIBE and Section 7.5 shows how the model was applied to the London bombings scenario. Section 7.6 discusses the (formal) comparison between the simulation runs and the formalised statements and Section 7.7 concludes the chapter with a discussion.

7.2 London Bombings
The London bombings of July 7, 2005 (also referred to as 7/7) involved 4 suicide bombers triggering explosions on the London Underground and Bus transport network. Two of these bombings took place on underground trains outside Liverpool Street and Edgware Road stations and a third one between King’s Cross and Russell Square. These bombs went off at around 8:50 in the morning during the ‘rush hour’ when most commuters travel to their workplaces. The fourth bomb went off on a double-decker bus at Tavistock Square about an hour later. 52 people were killed and more than 770 were injured, see [12].

7.3 Formalisation of Survivor Statements
Below, Section 7.3.1 describes how statements of survivors of the attack were obtained, and Section 7.3.2 explains how these were converted to formal notation.

7.3.1 Survivor Statements
The July 7 Review Committee was set up to ‘identify the successes and failings of the response to the bombings and to help improve things for the future…’ [12] and submitted its report to the London Assembly in June 2006. Information from nearly 85 individuals was obtained as part of this report to the London Assembly. These accounts consist of unstructured narratives from individuals involved in the incident and run into 299 pages of text. Of these, 21 are fairly detailed accounts of the experiences of the respective survivors depending on the proximity to the explosion of the concerned survivor, the evacuation process and after-effects on survivors including the psychological. 12 accounts relate to a public hearing held on 23 March 2006 and 9 relate to private meetings with the chairman of the Review Committee. The rest of the
accounts consist of information provided by survivors and affected persons through email and letters.

The July 7 Review Committee also obtained information and views from nearly 40 organisations. These accounts consist of unstructured narratives and written submissions of officials from a broad range of organisations including the police, fire brigade, ambulance, hospitals, local authorities, telecommunication companies and business associations and run into 284 pages of text. For the purposes of this chapter, only transcripts of individual survivors in their original form have been included in the analysis.

Statements of survivors are publicly accessible and available as a consolidated Volume 3 of the July 7 Review Report, in pdf as well as rich text format. The statements have been anonymised and so the names in the statements do not refer to the actual identity of the survivor. An example of a transcript of a survivor given the name ‘John’ and who was at the Edgeware Road Station site of the bombings, is shown in Figure 7.1 below.

Once again, can I thank you all for coming? John from Edgware Road. I believe you are going to start the proceedings.

**John (Edgware Road):** Thank you. Just after the train left Edgware station, there was a massive bang followed by two smaller bangs and then an orange fireball. I put my hands and arms over my ears and head as the windows and the doors of the carriage shattered from the blast. Splintered and broken glass flew through the air towards me and other passengers. I was pushed sideways as the train came to a sudden halt. I thought I was going to die. Horrific loud cries and screams filled the air, together with

![Fig. 7.1. Extract from John’s transcript at the July 7 Review](image)

The transcript was parsed into phrases that as far as possible conveyed a single idea leaving the statement in its original form. These phrases were treated as indications for ‘cues’ that help explain the behaviour and thoughts of the survivor. References to the location, time and time elapsed were also put alongside the cues. These have been either explicitly stated or inferred from surrounding statements in the transcript for the survivor. Each of the phrases was then formalised according to the scheme explained in the following subsection. An extract from the parsing table for ‘John’s transcript’ is shown below in Figure 7.2.
7.3.2 Formalisation

As a first step towards formalisation of the survivor statements, a time stamp has been assigned to each cue. Since little information is known about the actual time and duration of the events, we simply used natural numbers to describe the timing of the subsequent events (i.e., we say that they took place at time point 0, 1, 2, and so on). After that, the contents of the cues were analysed in more detail, to make an inventory of the classes of concepts they refer to. In general, each cue turned out to refer either to a belief or an action. Moreover, each belief or action turned out to belong either to the survivor himself, or another individual at the scene. For example, the statement ‘there was a massive bang’ refers to a belief of the speaker himself (namely that a blast had occurred), whereas the statement ‘I put my hands and arms over my ears and head’ refers to an action of the speaker. Similarly, the statement ‘a young woman sitting next to me asked me if I was OK’ refers to an action of another individual. Furthermore, with respect to the beliefs, two types of belief could be distinguished, namely beliefs that are triggered by an external stimulus (e.g., ‘there was a massive bang’) and beliefs that are triggered by an internal stimulus or thought (e.g., ‘I thought I was going to die’).

Based on this analysis of the contents of the cues, a formal domain ontology (or signature) has been developed. For this purpose, the LEADSTO language has been used, which is an extension of order-sorted predicate logic [4]. In this language, the domain under analysis can be described in terms of sets of sorts and subsorts relations, constants in sorts, functions, and logical predicates over sorts. An overview of the domain ontology developed for the current case study is provided in Table 7.1. Note that the predicates have been
chosen in such a way that they can be easily mapped onto concepts in AScribe. These predicates have generic names. The elements of the sorts are domain-specific, and depend on the particular scenario.

Table 7.1. Domain Ontology

<table>
<thead>
<tr>
<th>Predicate</th>
<th>Informal meaning</th>
</tr>
</thead>
<tbody>
<tr>
<td>has_belief(a:AGENT, b:BELIEF)</td>
<td>agent a has belief b</td>
</tr>
<tr>
<td>has_internal_belief(a:AGENT, b:BELIEF)</td>
<td>agent a has (internally triggered) belief b</td>
</tr>
<tr>
<td>performed(a:AGENT, ac:ACTION)</td>
<td>agent a performs action ac</td>
</tr>
</tbody>
</table>

After development of the domain ontology, the actual formalisation of the cues took place. To this end, for each survivor, the following algorithm was performed (described in pseudo-code):

```
start with an empty specification
for t = time step 1 to last-time do
  1. determine whether the cue at time t refers to a belief (either ‘internal’ or ‘external’) or action
  2. determine to which agent the cue belongs
  3. select the appropriate predicate from the domain ontology
  4. express the cue formally using that predicate, and add the result to the specification, annotated with time step t
end
```

As an illustration, Figure 7.3 shows (a visualisation of) the resulting formalisation of the survivor statement that was shown in Figure 7.1, in an example trace. In this figure, which contains a fragment of 30 time steps, time is on the horizontal axis; a box on top of a line indicates that an event is true at that time point.

As a final step, the events included in the formal traces needed to be connected to concepts within AScribe, enabling us to apply the model to the scenarios under investigation. The main concepts present in AScribe are beliefs, intentions, and emotions, which may be related either to specific world states or to decision options (see Section 7.4 for details). Thus, as an example, the ‘external beliefs’ were translated into ‘beliefs about the positiveness of the situation’ and ‘belief options’ in AScribe, the ‘internal beliefs’ were translated
into ‘emotions’ (of fear) in ASCRIBE, and the ‘actions’ were translated into ‘intention options’ in ASCRIBE. For the belief options and intention options, two types of actions were distinguished, namely ‘protective actions’ (e.g., covering one’s ears) and ‘social actions’ (e.g., comforting another passenger). Moreover, during these translations, numerical values (from the set \{0, 0.1, 0.2, \ldots, 0.9, 1\}, where 0.5 represents a neutral value) have been assigned to the strength of each state. For example, the belief that a blast has occurred clearly refers to a very negative situation (e.g., value 0.1), whereas the belief that help is underway refers to a positive situation (e.g., value 0.9). To guarantee inter-observer reliability, as a pre-test, part of the survivor statements have been formalised separately by two different observers. When comparing the results of the two formalisations, the differences turned out to be small: besides minor interpretation errors, the distance between the numerical scores of the two observers never were greater than 0.2.

An example of the outcome of this final step is shown in Figure 7.4. Note that this figure corresponds to the same scenario as Figure 7.3, but that a larger fragment (of 70 time steps) has been taken. As shown in the first graph, the positiveness of this agent (named John) fluctuates during the scenario. Initially (i.e. right after the explosion), he has some rather negative beliefs about the situation, but based on the development of the events, he starts to have some more positive beliefs from time point 20. The same pattern is repeated in the period between time point 40 and 70. Similarly, the other graphs show John’s level of emotion (fear in this case), and the extent to which his actions are ‘protective’ or ‘social’ actions. Note that the graphs only show some values in case the information is available; at the other time points nothing is shown. In Section 7.5, these kinds of information will be used in order to simulate the scenarios. In particular, the information shown in the first graph (beliefs about the situation) will be used as input for ASCRIBE, whereas the information of the other three graphs (emotions, protective and social actions) will be used to compare with the output of the model.
Fig. 7.3. Example formal trace – Qualitative information

Fig. 7.4. Example formal trace – Quantitative information
7.4 Simulation Model

To simulate the dynamics of beliefs, emotions and intentions of individuals involved in the 7/7 London bombings of 2005, the agent-based model ASCRIBE [9] was used and implemented in Matlab. For a complete overview of ASCRIBE, see [9]. In this section, the model is only briefly summarised, and is explained how it was tailored especially to the 7/7 London bombings case. The main concepts present in the original model ASCRIBE [9] are beliefs, intentions, and emotions. For the current purpose, the following specific states for the agents were taken, namely 1 emotional state per agent (fear), 2 intentional states per agent (either to perform a protective or social action) and 3 beliefs (one about the ‘positiveness’ of the situation and two about if an agent should perform a protective or social action):

- Fear of agent $A$: $q_{\text{fear}A}(t)$
- Intention indication for action option $O$ of agent $A$: $q_{\text{intention}(O)A}(t)$
- Belief in $X$ (either about situation or action) of agent $A$: $q_{\text{belief}(X)A}(t)$

In Figure 7.5, which is adapted from [9], an overview of the interplay of these different states within the model is shown. It is assumed that at the individual level the strength of an intention for a certain action option depends on the person’s beliefs (cognitive responding) in relation to that option. It is assumed that beliefs may generate certain emotions (affective responding), for example of fear, that in turn may affect the strength of beliefs (affective biasing). Note that it is assumed that these latter emotions are independent of the different action options. The contagion of all the different states between individuals is based on the concept of a mirror neuron (e.g., [10, 11]) which comes from Neuroscience. When states of other persons are mirrored by some of the person’s own states, which at the same time play a role in generating their own behaviour, then this provides an effective basic mechanism for how in a social context persons fundamentally affect each other’s mental states and behaviour.

Note that all mirroring processes take place through interaction between agents, whereas the other processes shown in Figure 7.5 occur internally, within an individual agent. An overview of the different intra- and interpersonal interaction processes is given in Table 7.2.

The central idea of the model is based upon the notion of contagion strength $\gamma_{SB,A}$ which is the strength with which an agent $B$ influences agent $A$ with respect to a certain mental state $S$ (which, for example, can be an emotion, a belief, or an intention). It depends on the expressiveness ($e_{SB}$) of the sender $B$, the strength of the channel ($\alpha_{SB,A}$) from sender $B$ to receiver $A$ and the openness ($\delta_{SA}$) of the receiver: $\gamma_{SB,A} = e_{SB} \alpha_{SB,A} \delta_{SA}$. The level $q_{SA}$ for mental state $S$ of agent $A$ is updated using the overall contagion strength of all agents $B$ not equal to agent $A$: $q_{SA} = \sum_{B \neq A} \gamma_{SB,A}$. Then the weighed external impact $q_{SA}^*$: for the mental state $S$
of all the agents $B$ upon agent $A$, is determined by: $q_{SA}^* = \sum_{B \neq A} \gamma_{SBA} q_{SB} / \gamma_{SA}$. Given these, state $S$ for an agent $A$ is updated by:

$$q_{SA}(t+\Delta t) = q_{SA}(t) + \psi_{SA} \gamma_{SA} \left[ f(q_{SA}^*(t), q_{SA}(t)) - q_{SA}(t) \right] \Delta t$$

Here $\psi_{SA}$ is an update speed factor for $S$, and $f(V_1, V_2)$ a combination function. This expresses that the value for $q_{SA}$ is defined by taking the old value, and adding the change term, which basically is based on the difference between $f(q_{SA}^*(t), q_{SA}(t))$ and $q_{SA}(t)$. The change also depends on two factors: the overall contagion strength $\gamma_{SA}$ (i.e., the higher this $\gamma_{SA}$, the more rapid the change) and the speed factor $\psi_{SA}$.

![Diagram](image)

**Fig. 7.5.** The interplay of beliefs, emotions and intentions in the 7/7 London bombings social context

<table>
<thead>
<tr>
<th>From $S$</th>
<th>To $S'$</th>
<th>Type</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>belief($X$)</td>
<td>fear</td>
<td>internal</td>
<td>affective response on information; for example, on threats and possibilities to escape</td>
</tr>
<tr>
<td>fear</td>
<td>fear</td>
<td>interaction</td>
<td>emotion mirroring by nonverbal and verbal interaction; for example, fear contagion</td>
</tr>
<tr>
<td>fear</td>
<td>belief($X$)</td>
<td>internal</td>
<td>affective biasing; for example, adapting openness or expressiveness</td>
</tr>
<tr>
<td>belief($X$)</td>
<td>belief($X$)</td>
<td>interaction</td>
<td>belief mirroring by nonverbal and verbal interaction; for example, of information on threats and action options</td>
</tr>
<tr>
<td>belief($X$)</td>
<td>intention($O$)</td>
<td>internal</td>
<td>cognitive response on information; for example, aiming for a protective action based on the danger of the situation</td>
</tr>
<tr>
<td>intention($O$)</td>
<td>intention($O$)</td>
<td>interaction</td>
<td>intention mirroring by nonverbal and verbal interaction; for example, of tendency to aim for a social action</td>
</tr>
</tbody>
</table>

Within the definition of the combination function $f(V_1, V_2)$ a number of further personality characteristics determine the precise influence of the contagion. First, a factor $\eta_{Sst}$ is distinguished which expresses the tendency of
an agent to absorb or amplify the level of a state $S$, whereas another personality characteristic $\beta_{SA}$ represents the bias towards reducing or increasing the value of the state $S$. Thus, the combination function $f(V_1, V_2)$ is defined as follows:

$$f(V_1, V_2) = \eta_{SA} \left[ \beta_{SA} (1 - (1 - V_1)(1 - V_2)) + (1 - \beta_{SA}) V_1 V_2 \right] + (1 - \eta_{SA}) V_1 \tag{2}$$

In ASCRIBE, the effects of emotions on beliefs are being calculated with the formulas in Section 4.1 of [9]. Instead of using these formulas here, the values for the beliefs about the situation and action options were taken from the empirical data as explained in Section 7.2 and 7.3. Hereby, we assume the effects of emotions on beliefs are implicitly present in these input values.

The effect of the emotion fear on beliefs is expressed by the following formula:

$$q_{fear,A}(t) = \nu_{A} \cdot (\sum_{B \neq A} \gamma_{fearBA} \cdot q_{fearB} / \gamma_{fearA}) + (1 - \nu_{A}) \cdot (\sum_{X} \omega_{X,fear,A} \cdot (1 - p_{XA}) \cdot r_{XA} \cdot q_{belief(X)}A) \tag{3}$$

In formula 3, information has an increasing effect on fear if it is relevant and non-positive, through informational state characteristics $r_{XA}$ denoting how relevant, and $p_{XA}$ denoting how positive information $X$ is for person $A$. The influence depends on the impact from the emotion fear by others (the first factor, with weight $\nu_{A}$) in combination with the influence of the belief present within the person. This $q_{fear,A}(t)$ is used in the equation describing the dynamics of fear:

$$q_{fearA}(t+\Delta t) = q_{fearA}(t) + \gamma_{fearA} \left[ f(q_{fearA}^*, q_{fearA})(t) - q_{fearA}(t) \right] \Delta t$$

with

$$f(q_{fearA}^*, q_{fearA})(t) = \eta_{fearA} \left[ \beta_{fearA} (1 - (1 - q_{fearA}^*(t))(1 - q_{fearA}(t))) + (1 - \beta_{fearA}) q_{SA}(t) q_{SA}(t) \right] + (1 - \eta_{fearA}) q_{fearA}(t)$$

Furthermore, the specific state $q_{emotion(O)}A$ was left out of the current model, since this state was not mentioned in the survivor reports and not realistic to use in the simulations. Therefore the effects of emotions on intentions in ASCRIBE is left out the current model, leaving the effect of beliefs on intentions calculated as follows:

$$q_{belief(O)}A(t) = \sum_{X} \omega_{X,O} q_{belief(X)}A / \sum_{X} \omega_{X,O}$$

where $\omega_{X,O}$ indicates how supportive information $X$ is for option $O$. The combination of the group’s aggregated intention with an agent’s own belief for option $O$ is made by a weighted average of the two:

$$q_{intent(O)}A^*(t) = (\omega_{O,BA} / \omega_{O,BA}) q_{intent(O)}A^*(t) + (\omega_{O,BA} / \omega_{O,BA}) q_{belief(O)}A(t) \tag{4}$$

$$q_{intent(O)}A = \omega_{O,BA} q_{intent(O)}A + \omega_{O,BA} q_{intent(O)}A \tag{5}$$

where $\omega_{O,BA}$ and $\omega_{O,BA}$ are the weights for the contributions of the group intention impact (by mirroring) and the own belief impact on the intention of $A$ for $O$, respectively, and
\[ \omega_{OIBA} = \omega_{OIA} + \omega_{OBA} \]

The overall model for the dynamics of intentions for options becomes:

\[ q_{\text{intention}(O)A}(t + \Delta t) = q_{\text{intention}(O)A}(t) + \gamma_{\text{intention}(O)A}^* \left[ \eta_{\text{intention}(O)A} \beta_{\text{intention}(O)A} (1 - \beta_{\text{intention}(O)A}(1 - q_{\text{intention}(O)A}(t))) + (1 - \eta_{\text{intention}(O)A}) q_{\text{intention}(O)A}(t) \right] \cdot \Delta t \]

### 7.5 Simulation Results

Multiple survivor reports of the London bombings at 7-7-2005 were formalised, as described in Section 7.2 and 7.3. As an illustration, in this section the simulation results of the use of ASCRIBE for one particular instance of this data is shown, namely for the scenario described in Section 7.3, involving the survivor named John. In the survivor report of John, the beliefs, emotions and intentions of 3 other persons were mentioned as well, therefore the simulation in Matlab was made for 4 agents in total. The beliefs of the situation and for the two action options (social action or protective action) were taken as inputs of the model. The fear value of John, and the values for his intentions to act in a protective or social manner, were produced by ASCRIBE as outputs. These output values (all between 0 and 1) are shown in Figure 7.6 and can be compared to the emotion fear and social and protective actions stated in the survivor report, which were formalised and are shown in Figure 7.4. The patterns in Figure 6, outputted by ASCRIBE, seem to correspond quite well with the patterns in the formalised empirical data from the survivor report in Figure 7.4. For example, in Figure 7.4 it can be seen that survivor John had a high fear level of 0.9 at three points in his report. In the left graph in Figure 7.6 it can be seen that through the interactions with the other agents and the internal affective responding, agent John also has a high fear value, fluctuating between 0.7 and 0.9. The right graph in Figure 7.6 shows that at the beginning, John is aiming more for protective actions than social actions, which seems logical in a dangerous situation. Over all time steps, John shows a decrease in his aim for protective actions in the first 10 time steps, followed by an increase till time step 15 and than another decrease till time step 30. This pattern can also be seen in Figure 7.4, where John’s stated protective actions in his report started high, decreased, increased and decreased. In Figure 7.4 can also be seen that John stated that he performed social actions, formalised by the value 0.6, around time steps 20-25 and 60-70. Figure 7.6 shows that ASCRIBE as well outputs social actions around the value 0.6, around time steps 20-25 and 60-70. The difference between Figure 7.4 and Figure 7.6 is, that in Figure 7.6 all values change dynamically over time, they are continuous, and in Figure 7.4 the values are only available for certain points in time, taken from the survivor report. As a consequence, the total pattern of
the real world data is not directly visible in the formalisation, like in Figure 7.4, but is visible when simulated by ASCRIBE. To further validate ASCRIBE against the real world data, a formal check was performed, where the real world data and the simulation results from ASCRIBE were compared automatically. This is explained in the next section.

Fig. 7.6. The values for fear and intentions for actions of survivor John

7.6 Formal Comparison
To formally compare the simulation results in Section 7.5 with the formalised transcripts presented in Section 7.3.2, the TTL Checker Tool [3] has been used. This piece of software enables the researcher to check whether certain expected (dynamic) properties, expressed as statements in the Temporal Trace Language (TTL) [3], hold for a given trace (defined as a time-indexed sequence of states). Since the tool can take both simulated and empirical traces as input, it can be used to check (automatically) whether the generated simulation runs show similar patterns as the real world transcripts.

Using the TTL Checker Tool, a number of dynamic properties have been verified against the traces described in Section 7.3.2 and 7.5 (to which we will refer as empirical traces and simulation traces, respectively). Some of these properties are presented below. To enhance readability, they are represented here in an informal notation, instead of a formal TTL notation. Note that the letters mentioned between the round brackets are parameters, which can be filled in when checking the property using the Checker Tool.

P1(a:agent, i1,i2:interval, m:trace) - ‘More positiveness implies more social actions’
For intervals i1 and i2 within trace m, if the average positiveness of agent a’s beliefs about the situation is higher in i1 than in i2, then agent a will perform more social actions in i1 than in i2.
**P2(a:agent, i1,i2:interval, m:trace) - ‘More positiveness implies less protective actions’**

For intervals i1 and i2 within trace m, if the average positiveness of agent a’s beliefs about the situation is higher in i1 than in i2, then agent a will perform more protective actions in i2 than in i1.

These dynamic properties (among several others, which are not shown due to space limitations) have been checked against the empirical and the simulation traces (where for all agents a, the interviewed persons were filled in). To create the intervals, all traces have been split up into relevant sub-scenarios (e.g., a part in which a person is present within a train carriage, or is present outside of the train), and each sub-scenario has been cut in two equal halves, which we call intervals. Thus, by checking property P1 and P2 for all sub-scenarios, we basically checked whether it was the case that people who became more positive during a sub-scenario stopped protecting themselves and started to help others, and vice versa. Surprisingly, this property turned out to hold for almost all sub-scenarios of the empirical traces. This is an interesting finding, which can be potentially explained by the phenomenon that positive people are more open to external stimuli [8]. In addition, the property turned out to hold for the simulated traces for the exact same sub-scenarios as in the empirical traces. Although this is obviously not an exhaustive proof for the correctness of ASCRIBE, it illustrates that the model can be used to reproduce similar patterns as found in realistic scenarios.

### 7.7 Discussion

In this chapter, it has been shown how the dynamics of individuals’ mental states in a real world incident can be analysed, through formalising survivor reports of the 7/7 London bombings in 2005 and evaluating them against generated simulations of the same case study with ASCRIBE. It is quite rare to work with this type of real world data of survivors of a terroristic attack, nevertheless, the ASCRIBE simulations in Section 7.5 showed that it can simulate corresponding patterns with those in the empirical data of the 7/7 London bombings. The formal check of dynamic properties in Section 7.6 also shows that the model ASCRIBE can be used to reproduce similar patterns as found in emergency scenario’s, like a terroristic attack.

So far, the results show that ASCRIBE can reproduce patterns in the dynamics of beliefs, intentions and emotions of people during a terroristic attack in the real world. The results are promising, and although the transcription work is quite time consuming, the current analysis model has been set up in a generic manner, which means large parts can be re-used for the analysis of other real world incidents or disasters.

The current chapter should mainly be seen as a proof-of-concept. The methodology turned out to be applicable to analysis of parts of the 7/7
bomings case study. In future work, the authors intend to analyse the reports
of a larger number of survivors, thereby better testing the robustness of the
model. In addition, a more extensive evaluation is planned, using a formal
measure for the correctness of the simulation results.

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Modelling the Interplay of Emotions, Beliefs and Intentions within


Part IV: Integrated Modelling of Contagion and Regulation of Negative Mood

Abstract. Part IV focuses on the networks of informal caregivers around persons with a depression. In Chapter 8, an agent model is proposed that can simulate the dynamics of informal care support and receipt interactions among caregivers and care recipients. Concepts like coping, strong ties in the social network and stress buffering showed to have important influences on the stress level of the informal caregiver. In Chapter 9, this work is extended, by proposing an intelligent support agent for informal caregivers. The intelligent agent can generate support actions for specific situations the informal caregiver is in, based on model-based reasoning. In Chapter 10, the integration of emotion regulation and emotion contagion was explored. The proposed agent-based model is innovative, because it integrated affective and cognitive processes. The model was specifically made for negative mood contagion and regulation. Simulations showed that the model is able to realistically produce the processes described in psychological and social literature. The models in Chapter 8, 9 and 10 were evaluated by automatic property checking and mathematical analysis.
Chapter 8 - Modelling Caregiving Interactions During Stress

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Abstract. Few studies describing caregiver stress and coping have focused on the effects of informal caregiving for depressed care recipients. The major purpose of this chapter was to investigate the dynamics of the informal care support and receipt interactions among caregivers and care recipients using a computational modelling approach. Important concepts in coping skills, strong ties support networks and stress buffering studies were used as a basis for the model design and verification. Simulation experiments for several cases pointed out that the model is able to reproduce interaction among strong tie network members during stress. In addition, the possible equilibria of the model have been determined, and the model has been automatically verified against expected overall properties.

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8.1 Introduction
Caring for a family member, spouse or friend (informal caregiving) who is diagnosed with a severe illness (e.g., a unipolar disorder) can be a stressful experience. While most caregivers adapt well to the situation of caring for a person with a unipolar depression, some do not. A number of studies investigate the negative consequences for the informal caregiver, such as the development of depression, burden, burnout, or (chronic) stress, when caring for elderly patients or patients with illnesses like dementia, or Parkinson’s [5], [6], [7], [9], [10]. The current chapter addresses the development of stress in informal caregivers of patients with unipolar depression and the effect of this stress on the interactions between the caregiver and care recipient. To understand the caregiver’s adaptations to the cognitive disabilities of his/her close acquaintance, the complex nature of stress processes must be accounted for and the constructs and factors that play a function in the caregiving must be considered. For each individual a number of cognitive and physiological mechanisms regulate the impact of stress on health and well-being. Individuals typically occupy multiple roles in life; becoming a caregiver of a person with depression introduces an additional role, and therefore will require some rearrangement of priorities, and redirection of energy [10]. Not only is this likely to produce strain at a personal level, but it is also likely to spur reactions (potentially negative) from diverse people who are interconnected to a person through his or her roles outside the realm of caregiving.

Although much work has been dedicated to understand the caregiving mechanism, little attention has been paid to a computational modelling angle on how caregivers work together to support their close acquaintances under stress. The caregiving process is highly dynamic in nature, and it requires demanding resources to monitor such a process in the real world [6]. The aim of this chapter is to present a computational model that can be used to simulate the dynamics in the caregiver and care recipient under influence of external events. The current work is an addition to our previous model of social support selection, where in the current model, individuals with a depressive state are receiving help from close acquaintances [1].

The chapter is organized as follows; Section 8.2 describes several theoretical concepts of social support networks and their relation to stress. From this point of view, a formal model is designed (Section 8.3). Later in Section 8.4, a number of simulation traces are presented to illustrate how the proposed model satisfies the expected outcomes. In Section 8.5, a mathematical analysis is performed in order to identify possible equilibria in the model, followed by verification of the model against formally specified expected overall patterns, using an automated verification tool (Section 8.6). Finally, Section 8.7 concludes the chapter.
Part IV: Integrated Modelling of Contagion and Regulation of Negative Mood

8.2 Underlying Principles in Informal Caregiving Interactions

Researchers from several domains have become increasingly interested in social support, caregiving, and mental health. For instance, researchers in nursing and healthcare domain have contributed several theories to explain those relationships by presenting foundations on coping behaviours, mediating attributes, caregiving adaptation, and stress. One of the theories that has been used to explain these interactions is the Theory of Caregiver Stress and Coping which combines important principles in Lazarus Stress-Coping Theory, Interpersonal Framework of Stress-Coping, and Stress Process Theory of Pearlin [3], [4], [11].

Within the model introduced, three aspects play important roles to regulate support and maintain the caregiver’s personal health: 1) externally generated stressors (negative events), 2) mediating conditions, and 3) caregiver outcomes [4], [6], [10]. For the first aspect, stressors are related to specific internal or external demands (primary stressors) that the caregiver has to manage. For example, several studies show that sufficient caregiver personal resources (e.g. financial incomes, social) reduces the perception of caregiving burden, while a loss of emotional resources (long term emotional exhaustion) amplifies the perceived burden [9]. The second aspect represents how the caregiver reacts (coping strategies) when facing the adversity in caregiving. In the proposed model, caregivers who face a primary stressful situation generally use a combination of problem-focused coping and emotion-focused coping. Problem-focused coping is associated with positive interpersonal efforts to get the problem solved [3]. In contrast to this, emotion-focused coping strategies (thinking rather than acting to change the person-environment relationship) entail efforts to regulate the emotional consequences (e.g. avoidance) of stressful or potentially stressful events [4]. This choice of coping is related to the caregiver’s personality, for example, a caregiver with a positive personality (e.g., low in neuroticism) tends to choose problem-focused approach [5]. Another important concept that can derived from these coping strategies is the relationship focused coping (positive or negative). The combination of high caregiver’s empathy (perceiving the inner feeling of care recipient) and problem-focused coping will lead to positive relationship coping, and vice versa [4], [7], [8]. The third aspect is related to the caregiver’s outcome. Mainly, this component ranges on a continuum from bonadaptation (meeting the needs to support the care recipient) to maladaptation (continued negative situation and need for referral and assistance) [4], [11]. In addition to this, bonadaptation is related to the high personal accomplishment (expected personal gain) and provided support (social support), while maladaptation is linked to the emotional exhaustion [9]. A high expected personal gain reduces the short term and long term stress level in caregivers, which will improve interaction during the caregiving process [7].
When the care recipients receive support, it will reduce their stress by the resource serves as an insulating factor, or stress buffer, so that people who have more social support resources are less affected by negative events [5], [6].

8.3 Modeling Approach
Based on the analysis of the dynamics in coping behaviours, mediating attributes, caregiving adaptation, and stress, as given in the previous section, it is possible to specify computational properties for the multi-agent model. The results from the interaction between these variables form several relationships, both in instantaneous and in temporal form. To represent these relationships in agent terms, each variable will be coupled with an agent’s name (A or B) and a time variable t. When using the agent variable A, this refers to the caregiver agent and B to the care recipient agent. This convention will be used throughout the development of the model in this chapter. The details of this model are shown in Fig. 8.1.
8.3.1 The Caregiver Model

This component of the overall model aims to formalise important concepts within the caregiver. The instantaneous relationships are expressed as follows. The problem-focused coping $PfC$ is calculated using the combination of the caregiver personality $GpP$ and burden $Bd$. Note that a high burden level close to 1 will have the effect that the choice of using problem focused coping becomes smaller.

$$PfC_A(t) = GpP_A(t).(1-Bd_A(t)) \tag{1}$$

$$EfC_A(t) = (1-GpP_A(t)).Bd_A(t) \tag{2}$$

However in emotional-focused coping $EfC$, those factors provide a contrasting effect. Positive relationship focused coping ($RfC+$) depends on the relation between problem focused coping and caregiver’s empathy. A high empathy will increase this function, while reducing its counterpart (negative relationship focused coping ($RfC-$)).

$$RfC_A^+ = PfC_A(t).GE_A(t) \tag{3}$$

$$RfC_A^- = EfC_A(t).(1-GE_A(t)) \tag{4}$$

Burden ($Bd$) is determined by regulating proportional contribution $\beta$ between caregiver primary stressors ($GpS$), long term emotional exhaustion ($ExH$), and caregiver resources ($GpR$). Expected personal gain ($PgN$) is measured using the proportional contribution (determined by $\sigma$) of the bonadaption ($Bn$) and experienced personal satisfaction $EpN$. Short term emotional exhaustion $EsH$ is measured by combining maladaptation $Md$ and negative relationship of expected personal gain.

$$Bd_A(t) = \beta.GpS_A(t)+(1-\beta).ExH_A(t).Bd_A(t) \tag{5}$$

$$PgN_A(t) = \sigma.Bn_A(t) + (1-\sigma).EpN_A(t) \tag{6}$$

$$EsH_A(t) = Md_A(t)+(1-PgN_A(t)) \tag{7}$$

Caregiver short term stress $GsS$ is related to the presence of caregiver negative events $GnE$ and burden $Bd$. Note that a high expected personal gain will reduce the short term stress level. The maladaptation $Md$ is calculated using the combination of negative ($RfC^-$), positive, relationship, and emotional-focused coping. In the case of bonadaptation, it is determined by measuring the level of positive, negative, relationship, and problem-focused coping. Parameters $\phi$, $\gamma$, and $\rho$ provide a proportional contribution factor in respective relationships. In addition to the instantaneous relations, there are four temporal relationships involved, namely experienced personal satisfaction $EpN$, long term emotional exhaustion $ExH$, caregiver long term stress $GlS$, and social support $ScP$. The rate of change for all temporal relationships are determined by flexibility rates, $\gamma$, $\delta$, $\varphi$, and $\psi$, respectively.

$$GsS_A(t) = \phi.GnE_A(t) + (1-\phi).Bd_A(t) \tag{8}$$

$$Md_A(t) = \gamma.RfC_A^-+\gamma.EfC_A(t) \tag{9}$$

$$Bn_A(t) = \rho.RfC_A^+ \tag{10}$$

The current value for all of these temporal relations is related to the previous respective attribute. It should be noted that the change process is measured in
a time interval between \( t \) and \( t+\Delta t \). The operator \( \text{Pos} \) for the positive part is defined by \( \text{Pos}(x) = (x + |x|)/2 \), or, alternatively; \( \text{Pos}(x) = x \) if \( x \geq 0 \) and \( 0 \) else.

\[
\begin{align*}
\text{ExHA}(t+\Delta t) &= \text{ExHA}(t) + \gamma \cdot \text{Pos}(\text{EsHA}(t) - \text{ExHA}(t)) \cdot (1-\text{ExHA}(t)) - \\
&\quad \text{Pos}(\text{EsHA}(t) - \text{ExHA}(t)) \cdot \text{ExHA}(t)) \\
\text{EpNA}(t+\Delta t) &= \text{EpNA}(t) + \vartheta \cdot \text{Pos}(\text{ScpA}(t) - \text{GpSA}(t) - \text{EpNA}(t)) \cdot (1-\text{EpNA}(t)) - \\
&\quad \text{Pos}(\text{ScpA}(t) - \text{GpSA}(t) - \text{EpNA}(t)) \cdot \text{EpNA}(t)) \\
\text{GlSA}(t+\Delta t) &= \text{GlSA}(t) + \varphi \cdot (\text{GsSA}(t) - \text{GlSA}(t)) \cdot \text{GlSA}(t) \\
\text{ScPA}(t+\Delta t) &= \text{ScPA}(t) + \psi \cdot \text{Pos}(\text{PgNA}(t) - \text{ScPA}(t)) \cdot (1-\text{ScPA}(t)) - \\
&\quad \text{Pos}(\text{PgNA}(t) - \text{ScPA}(t)) \cdot \text{ScPA}(t))
\end{align*}
\]

8.3.2 The Care Recipient Model

The care recipient model is another interacting components in the overall model. It has five instantaneous relations (care recipient perceived stress \( R_{pS} \), stress buffer \( S_{bF} \), care recipient short term stress \( R_{sS} \), care recipient functional \( R_{fS} \) and behavioural status \( R_{bS} \)) and one temporal relation (care recipient long term stress \( R_{lS} \)).

\[
\begin{align*}
R_{pS}(t) &= \tau \cdot R_{nI}(t) + (1-\tau) \cdot R_{nE}(t) \\
S_{bF}(t) &= \alpha \cdot R_{Gn}(t) \\
R_{sS}(t) &= \lambda \cdot R_{pS}(t) + (1-\lambda) \cdot R_{R_{sS}(t)}, R_{S_{bF}(t)} \cdot R_{lS}(t) \\
R_{fS}(t) &= R_{hS}(t) \cdot R_{lS}(t) \\
R_{bS}(t) &= R_{pS}(t) \cdot R_{lS}(t) \\
R_{lS}(t+\Delta t) &= R_{lS}(t) + \frac{\eta}{R_{lS}(t)-R_{S_{bF}(t)}; (1-R_{lS}(t)) \cdot R_{lS}(t) \cdot \Delta t}
\end{align*}
\]

Care recipient perceived stress is modelled by instantaneous relations (regulated by a proportional factor \( \tau \)) between the care recipient negative interactions \( R_{nI} \) and events \( R_{nE} \). Stress buffer is determined by \( \omega \) times received support \( R_{S_{b}} \). Care recipient short term stress depends on the relation between stress buffer \( S_{bF} \), and the proportion contribution \( \lambda \) of care recipient coping skills \( R_{C_{S}} \), perceived stress \( R_{pS} \), and negative personality \( R_{pS} \). For the care recipient functional and behaviour status levels, both of these relations are calculated by multiplying the value of care recipient health problem status \( R_{hS} \) and negative personality \( R_{p} \) with care recipient long term stress \( R_{lS} \) respectively. In addition, the temporal relation of care recipient long term stress is contributed from the accumulation exposure towards care recipient short term stress with the flexibility rate \( \eta \).

8.4 Simulation Results

In this section, a number of simulated scenarios with a variety of different conditions of individuals are discussed. Only three conditions are considered: prolonged, fluctuated stressor, and non-stressful events with a different personality profile. For clarity, \( cg \) and \( cr \) denotes caregiver and care recipient agent profiles respectively. The labels ‘good’ and ‘bad’ in Table 8.1 can also be read as ‘effective’ and ‘ineffective’ or ‘bonadaptive’ and ‘maladaptive’.
Table 8.1: Individual Profiles

<table>
<thead>
<tr>
<th>Caregiver</th>
<th>GpR</th>
<th>GE</th>
<th>GpP</th>
</tr>
</thead>
<tbody>
<tr>
<td>cg1 ('good' caregiver)</td>
<td>0.8</td>
<td>0.7</td>
<td>0.7</td>
</tr>
<tr>
<td>cg2 ('bad' caregiver)</td>
<td>0.1</td>
<td>0.2</td>
<td>0.2</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Care recipient</th>
<th>RhS</th>
<th>Rp</th>
<th>RcS</th>
</tr>
</thead>
<tbody>
<tr>
<td>cr1 ('good' coping skills)</td>
<td>0.9</td>
<td>0.9</td>
<td>0.8</td>
</tr>
<tr>
<td>cr2 ('bad' coping skills)</td>
<td>0.9</td>
<td>0.9</td>
<td>0.1</td>
</tr>
</tbody>
</table>

Corresponding to these settings, the level of severity (or potential onset) is measured, defining that any individual that scored more than 0.5 in their long term stress level (within more than 336 time steps) then the caregiver or support receipt agent will be experiencing stress. There are several parameters that can be varied to simulate different characteristics. However, the current simulations used the following parameters settings: \(t_{max}=1000\) (to represent a monitoring activity up to 42 days), \(\Delta t=0.3\), (flexibility rate) \(\varphi=\eta=\beta=\psi=\vartheta=0.3\), (regulatory rate) \(\alpha=\beta=\gamma=\rho=\sigma=\phi=\tau=0.5\), \(\omega=\xi=0.8\). These settings were obtained from previous systematic experiments to determine the most suitable parameter values in the model.

Result # 1: Caregiver and receiver experience negative events. During this simulation, all agents have been exposed to an extreme case of stressor events. This kind of pattern is comparable to the prolonged stressors throughout a life time. For the first simulation trace (Fig. 8.2(a)), a good
caregiver tends to provide a good social support provision towards its care recipient even facing persistent heighten stressors. This pattern is in line with the findings reported in [5]. One of the factors can be used to explain this condition is the increasing level of caregiver’s personal gain. It proposes that caregivers do not unequivocally view caregiving as an overwhelmingly negative experience but can appraise the demands of caregiving as rewarding [4], [9]. Previous research works has also suggests that caregiving satisfaction is an important aspect of the caregiving experience and seem to share parallel relationships with other variables (e.g, personality and empathy) [4], [11]. Moreover, a good caregiver normally uses a problem focused coping to solve the perceived problem and later increases positive relationship focused coping. By the same token, research has consistently established a significant relationship between personal gains, problem focused coping, and positive social support. For example, several studies reported that caregivers who were satisfied with caregiving used more problem-focused coping [3]. Having this in motion, it provides a positive view of social support and later will be translated as a support received by the care recipient.

![Graph](image_url)

**Figure 8.3:** Simulation traces during different stressors for (a, upper graph) a good caregiver and bad care recipient (b, lower graph) a bad caregiver and bad recipient

In the second simulation trace (as shown in Fig. 8.2(b)), both agents (caregiver and care recipient) are facing high long term stress levels in the long run. The precursors of having these conditions are perception of caregiving as a burden and the inability of the caregiver to provide positive coping during stressful events [11]. These factors lead to the decreasing level of caregiver’s positive
relationship focused coping and experienced personal gain, and later will reduce the ability to provide support. Additionally, in the real world, it can be perceived as feeling overwhelmed and out of control of the situation. This condition occurs almost within the majority of caregivers when they feel burdened by the demands of caregiving [6].

**Result # 2: Caregiver and receiver experience different types of negative events.** In this simulation, a new kind of stressor was introduced. This stressor comprises two parts: the first part is one with very high constant prolonged stressors, and is followed by the second one, with a very low stressor event. During simulation, the caregiver agents (cg1 and cg2) were exposed towards these stressors, while the care recipient agents will only experience prolonged stressors. As it can be seen from Fig. 8.3(a), the graph indicates both agents (cg1 and cr2) experience gradual drops in their long term stress. Comparison between Fig. 8.3(a) and Fig. 8.3(a), shows that the scenario’s almost have a similar pattern, but 3(a) has a substantial decrease in a caregiver’s long term stress level after the first half of the simulation. It is consistent with the findings that caregivers with a positive personality, empathic, and high personal resources tend to help more if they experienced less negative event [3], [8]. Meanwhile, Fig. 8.3(b) provides different scenarios. The simulation results show that caregivers with a negative personality, less empathic, and low personal resources is incapable to provide support during caregiving process. Note that despite the caregivers experience non-stressor events after the first half of the simulation, their care recipient is still experiencing a high long term stress level. Similar findings can be found in [5], [10].

**Result # 3: Managing a good care recipient.** In this part, simulation was carried out to investigate the effects of the caregiving behaviours of caregiver agents with different profiles to good care recipients, during prolonged negative stressors. Interaction between good caregiver and recipient shows that both agents have low long term stress levels, while the recipients stress buffer and the caregiver’s expected personal gain are increasing [5], [7]. On the contrary, interaction between bad caregiver and good care recipient indicates that both agents are experiencing high long term stress levels. However, the care recipient experiences lesser long term stress compared to the caregiver.

### 8.5 Mathematical Analysis

In this section it is discussed which equilibria value are possible for the model, i.e., values for the variables of the model for which no change will occur. As a first step the temporal relations for both caregiver and care recipient will be inspected (refer to the equations (11), (12), (13), (14), and (20)).
An equilibrium state is characterised by: \( \text{ExHA}(t+\Delta t) = \text{ExHA}(t), \text{ScPA}(t+\Delta t) = \text{ScPA}(t), \text{GlSA}(t+\Delta t) = \text{GlSA}(t), \text{EpNA}(t+\Delta t) = \text{EpNA}(t), \) and \( \text{RlSB}(t+\Delta t) = \text{RlSB}(t) \). Assuming \( \gamma, \psi, \phi, \vartheta \) nonzero, and leaving out \( t \), this is equivalent to:

\[
\begin{align*}
\left[ \text{Pos}(\text{EsHA} - \text{ExHA})(1 - \text{ExHA}) - \text{Pos}(-\text{EsHA} - \text{ExHA}) \cdot \text{ExHA} \right] &= 0 \\
\left[ \text{Pos}(\text{PgNA} - \text{ScPA})(1 - \text{ScPA}) - \text{Pos}(-\text{PgNA} - \text{ScPA}) \cdot \text{ScPA} \right] &= 0 \\
(\text{GsSA} - \text{GlSA})(1 - \text{GlSA}) \cdot \text{GlSA} &= 0 \\
\left[ \text{Pos}(\text{ScPA} - \text{GpSA} - \text{EpNA})(1 - \text{EpNA}) - \text{Pos}(-\text{ScPA} - \text{GpSA} - \text{EpNA}) \cdot \text{EpNA} \right] &= 0 \\
(\text{RsSB} - \text{RlSB})(1 - \text{RlSB}) \cdot \text{RlSB} &= 0
\end{align*}
\]

These equations are equivalent to:

\[
\begin{align*}
\text{EsHA} - \text{ExHA} &= 0 \\
\text{PgNA} - \text{ScPA} &= 0 \\
\text{GsSA} - \text{GlSA} &= 0 \\
\text{ScPA} - \text{GpSA} - \text{EpNA} &= 0 \\
\text{RsSB} - \text{RlSB} &= 0 \\
\end{align*}
\]

These have the following solutions:

\[
\begin{align*}
\text{EsHA} &= \text{ExHA} \\
\text{PgNA} &= \text{ScPA} \\
\text{GsSA} &= \text{GlSA} \\
\text{ScPA} &= \text{EpNA} \\
\text{RsSB} &= \text{RlSB}
\end{align*}
\]

This means that for the caregiver short term and long term emotional exhaustion are equal (21). Also for both the caregiver and the care recipient short term and long term stress are the same, when the long term stress is not 0 or 1 (23) and (25). Moreover, for the caregiver social support provision is equal to expected personal gain (22), and on the other hand social support provision is equal to the sum of experienced personal gain and the caregiver’s primary stressors (24).

### 8.6 Formal Verification of the Model

This section addresses the analysis of the informal caregiving interactions model by specification and verification of properties expressing dynamic patterns that are expected to emerge. The purpose of this type of verification is to check whether the model behaves as it should by running a large number of simulations and automatically verifying such properties against the simulation traces. A number of dynamic properties have been identified, formalized in the language TTL and automatically checked [2]. The language TTL is built on atoms \( \text{state}(t, t) \models p \) denoting that \( p \) holds in trace \( \gamma \) (a trajectory of states over time). Dynamic properties are temporal predicate logic statements that can be formulated using such state atoms. Below, a some of the dynamic properties that were identified for the informal caregiving interactions model are introduced, both in semi-formal and in informal notation. Note that the properties are all defined for a particular trace \( \gamma \) or a pair of traces \( \gamma_1, \gamma_2 \).
**P1 – Stress level of cg**

For all time points $t_1$ and $t_2$ in traces $\gamma_1$ and $\gamma_2$

if in trace $\gamma_1$ at $t_1$ the level of negative life events of agent cg is $x_1$

and in trace $\gamma_2$ at $t_1$ the level of negative life events of agent CG is $x_2$,

and in trace $\gamma_1$ at $t_1$ the level of personal resources of agent cg is $y_1$

and in trace $\gamma_2$ at $t_1$ the level of personal resources of agent cg is $y_1$,

and in trace $\gamma_1$ at $t_1$ the level of long term stress of agent cg is $z_1$

and in trace $\gamma_2$ at $t_1$ the level of caregiver stress of agent cg is $z_2$,

and $x_1 \geq x_2$, and $y_1 \leq y_2$, and $t_1 < t_2$,

then $z_1 \geq z_2$.

$\forall \gamma_1, \gamma_2: \text{TRACE}, \forall t_1, t_2: \text{TIME} \forall x_1, x_2, y_1, y_2, z_1, z_2: \text{REAL}$

$\text{state}(\gamma_1, t_1) \models \text{negative}_\text{life}_\text{events}(\text{ag}(\text{cg}), x_1)$ & $\text{state}(\gamma_2, t_1) \models \text{negative}_\text{life}_\text{events}(\text{ag}(\text{cg}), x_2)$ & $\text{state}(\gamma_1, t_1) \models \text{personal}_\text{resources}(\text{ag}(\text{cg}), y_1)$ & $\text{state}(\gamma_2, t_1) \models \text{personal}_\text{resources}(\text{ag}(\text{cg}), y_1)$ & $\text{state}(\gamma_1, t_2) \models \text{long}_\text{term}_\text{stress}(\text{ag}(\text{cg}), z_1)$ & $\text{state}(\gamma_2, t_2) \models \text{long}_\text{term}_\text{stress}(\text{ag}(\text{cg}), z_2)$ & $x_1 \geq x_2$ & $y_1 \leq y_2$ & $t_1 < t_2$

$\Rightarrow z_1 \geq z_2$

Property P1 can be used to check whether caregivers with more stressful life events and lack of resources will experience a higher level of caregiver (long term) stress. The property succeeded when two traces were compared where in one trace the caregiver had more (or equal) negative life events and less personal resources than the caregiver from the other trace. In this situation the first caregiver experienced more long term stress than the caregiver with more personal resources and less negative life events. Notice that since this property checks whether it is true for all time points in the traces, in some simulation traces the values for negative life events or personal resources change halfway the simulation trace, then the property succeeds for only a part of the trace, which can be expressed by an additional condition stating that $t_1$ is at time point 500 (halfway our traces of 1000 time steps).

**P2 – Stress buffering of cr**

For all time points $t_1$ and $t_2$ in trace $\gamma$,

If at $t_1$ the level of received social support of agent cr is $m_1$

and $m_1 \geq 0.5$ (high) and at time point $t_2$ the level of the stress buffer of agent cr is $m_2$

and $t_2 \geq t_1+d$,

then $m_2 \geq 0.5$ (high).

$\forall \gamma: \text{TRACE}, \forall t_1, t_2: \text{TIME} \forall m_1, m_2, d: \text{REAL}$

$\text{state}(\gamma, t_1) \models \text{received}_\text{social}_\text{support}(\text{ag}(\text{cr}), m_1)$ & $\text{state}(\gamma, t_2) \models \text{stress}_\text{buffer}(\text{ag}(\text{cr}), m_2)$ & $m_1 \geq 0.5$ & $t_2 = t_1+d$

$\Rightarrow m_2 \geq 0.5$
Property P2 can be used to check whether social support buffers the care recipient’s stress. It is checked whether if the received social support in agent cr is high (a value higher or equal to 0.5), then the stress buffer of agent cr also has a high value after some time (having a value above or equal to 0.5). The property succeeded on the traces, where the received social support was higher or equal to 0.5.

Relating positive recovery of care receiver and social support from care giver

Property P3 can be used to check whether positive recovery shown by the care recipient, will make the caregiver provide more social support at a later time point. This property P3 can be logically related to milestone properties P3a and P3b that together imply it: P3a & P3b ⇒ P3. Given this, using the checker it can be found out why a hierarchically higher level property does not succeed. For example, when property P3 does not succeed on a trace, by the above implication it can be concluded that at least one of P3a and P3b cannot be satisfied. By the model checker it can be discovered if it is property P3a and/or P3b that does/do not succeed. Properties P3a and P3b are introduced after property P3 below.

P3 – Positive recovery of cr leads to more social support from cg

For all time points t1 and t2 in trace γ,

If at time point t1 the level of primary stressors of agent cg is d1
and at time point t2 the level of primary stressors of agent cg is d2
and at time point t1 the level of received support of agent cr is f1
and at time point t2 the level of received support of agent CR is f2
and d2 ≥ d1, and t1 < t2,
then f2 ≥ f1

∀γ:TRACE, ∀t1, t2:TIME ∀d1, d2, f1, f2:REAL
state(γ, t1) |= primary_stressors(ag(cg), d1) & state(γ, t2) |= primary_stressors(ag(cg), d2) &
state(γ, t1) |= received_social_support(ag(cr), f1) & state(γ, t2) |=
received_social_support(ag(cr), f2) &
d2 < d1 & t1 < t2
⇒ f2 ≥ f1

Property P3 succeeded in all generated simulation traces: when the primary stressors of the caregiver decreased, then at a later time point the received social support of the care recipient increased. In some simulation traces the property only succeeded on the first or second half of the trace. In these traces the primary stressors of the caregiver increased in the first part of the trace and then decreased in the second part of the trace. For this, a condition was added to the antecedent of the formal property, namely t1 = 500 or t2 = 500, so that the property is only checked on the second part or first part of the trace respectively.
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P3a – Positive recovery of cr leads to more personal gain in cg
For all time points t1 and t2 in trace γ,
If at t1 the level of primary stressors of agent cg is d1
and at time point t2 the level of primary stressors of agent cg is d2
and at time point t1 the level of personal gain of agent cg is e1
and at time point t2 the level of personal gain of agent cg is e2
and d2 ≤ d1, and t1 < t2
then e2 ≥ e1
∀γ:TRACE, ∀t1, t2:TIME ∀d1, d2, e1, e2:REAL
state(γ, t1) |= primary_stressors(ag(cg), d1) & state(γ, t2) |= primary_stressors (ag(cg), d2) &
state(γ, t1) |= expected_personal_gain(ag(cg), e1) & state(γ, t2) |= expected_personal_gain (ag(cg), e2) & d2 < d1 & t1 < t2
⇒ e2 ≥ e1

Property P3a can be used to check whether, the caregiver’s expected personal gain will increase, if the primary stressors of the caregiver decrease. This property succeeded on the simulation traces where the primary stressors of the caregiver indeed decreased.

P3b – Personal gain in cg motivates cg to provide more social support to cr
For all time points t1 and t2 in trace γ,
If at time point t1 the level of personal gain of agent cg is e1
and at time point t2 the level of personal gain of agent cg is e2
and at t1 the level of received support of agent cr is f1
and at time point t2 the level of received support of agent cr is f2,
and e2 ≥ e1, and t1 < t2,
then f2 ≥ f1
∀γ:TRACE, ∀t1, t2:TIME ∀e1, e2, f1, f2:REAL
state(γ, t1) |= expected_personal_gain(ag(cg), e1) & state(γ, t2) |= expected_personal_gain(ag(cg), e2) & state(γ, t1) |= received_social_support(ag(cr), f1) & state(γ, t2) |= received_social_support(ag(cr), f2) & e2 ≥ e1 & t1 < t2
⇒ f2 ≥ f1

Property P3b can be used to check whether the caregiver receives more social support if the expected personal gain of the caregiver increases. This property succeeded on the simulation traces where the expected personal gain indeed increased.

8.7 Conclusion
The challenge addressed in this chapter is to provide a computational model that is capable of simulating the behaviour of an informal caregiver and care recipient in a caregiving process when dealing with negative events. The proposed model is based on several insights from psychology, specifically
stress-coping theory, and informal caregiving interactions; see [3], [4].
Simulation traces show interesting patterns that illustrate the relationship between personality attributes, support provision, and support receiving, and the effect on long term stress. A mathematical analysis indicates which types of equilibria occur for the model. Furthermore, using generated simulation traces, the model has been verified against a number of properties describing emerging patterns put forward in the literature. The resulting model can be useful to understand how certain concepts in a societal level (for example; personality attributes) may influence caregivers and recipients while coping with incoming stress. In addition to this, it could be used as a mechanism to develop assistive agents that are capable to support informal caregivers when they are facing stress during a caregiving process. As part of future work, it would be interesting to expand the proposed model in a social network of multiple caregivers and care recipients.

References
Chapter 9 - An Ambient Agent Model for Support of Informal Caregivers During Stress

Azizi Ab Aziz, Jan Treur, C. Natalie van der Wal

Abstract. Caring for a depressed person may have substantial impact on the health and well-being of the caregiver. In this chapter, an ambient agent model is proposed that supports caregivers, to prevent or decrease the burden in them and promote their well-being. The agent integrates a domain model of the functioning of the caregiver and the care recipient and their interaction, and exploits model-based reasoning to assess the caregiver’s state in order to generate dedicated actions that are tuned to the circumstances.

This chapter will appear as:
9.1 Introduction
Ambient Intelligence applications in the health area usually focus on providing support for persons suffering from some disease or mental disorder (e.g., [1]). For the mental health area applications have been designed to monitor and support persons suffering from depression (e.g., [2]). However, often also persons in the daily environment of a depressed person are affected and may experience a heavy burden as an informal caregiver. In the therapeutic area also support for such informal caregivers, such as partners or family members has been developed; see, for example [7]. This chapter focuses on these informal caregivers.

An ambient agent model is presented to provide support to caregivers, based on monitoring and assessing the situation of both the caregiver and care recipient, and determining dedicated support actions. The ambient agent model uses a computational model for caregiving interactions, adopted from [3], and exploits model-based reasoning to monitor and assess the situation, and guidelines adopted from [7] in order to generate support actions (based on these assessments) that are tailored to the persons and their states.

In this chapter, first in Section 9.2 the adopted computational (domain) model for caregiving interactions is briefly described. Next, in Section 9.3 the ambient agent model integrating this domain model is presented. In Section 9.4 a number of simulation results for different types of scenarios are discussed. Section 9.5 addresses formal verification of simulation results. Finally, Section 9.6 is a discussion.

9.2 A Domain Model for Caregiving Interactions During Stress
In this section, the domain model used is presented. This dynamic model for informal caregiving interactions during stress was adopted from [3]. This model will serve as a basis for later use in an analysis and a support model. Fig. 9.1 depicts a global description of relevant states within the model and the relations between the states. In the figure, the states that are depicted in grey represent states that have been used as a monitoring component. In addition, the states in bold lines represent the point of impacts of support provided by an intelligent support agent.
Fig. 9.1. Overview of the Domain Model for Caregiving Interactions During Stress

Basically, there are three important aspects play vital roles to maintain social support and caregiver’s wellbeing, namely; (1) incoming stressors (from the environment (negative events), and care recipient (primary stressor)), (2) mediating conditions (coping, personal attributes), and (3) caregiver outcomes (emotional exhaustion, personal gain, stress, and support provision) [6]. In the model, a number of states have been defined, whereby each state is represented by a number between 0 (low) and 1 (high). In the previous model, two interconnected models (caregiver and care recipient models) were involved, however for the purpose of this chapter, only a caregiver model has been used in a detailed manner, and the recipient model has been used in a more abstracted form. To represent the relationships over time in agent terms, subscripts are used with an agent’s name $A$ (caregiver agent). In addition to this, the current value for all of these temporal relations is related to the previous respective attribute. Note that the change process is measured in a time interval between $t$ and $t+\Delta t$. The operator Pos for the positive part is defined by $\text{Pos}(x) = (x + |x|)/2$, or, alternatively; $\text{Pos}(x) = x$ if $x \geq 0$ and 0 else. First, the state of burden will be explained. The state burden ($B_d$) is used to express what caregiver feels when dealing with the combinations of primary stressor ($G_pS$), negative events ($N_gE$), and emotional exhaustion ($E_{xH}$). If the
Caregiver has adequate personal resources ($G_{pR}$), it will dampen the progress of burden level; otherwise it will lead to the formation of *caregiver’s short-term stress* ($G_{sS}$), and later will build up as *caregiver’s long-term stress* ($G_{lS}$).

$$Bd_{A}(t) = [\beta G_{pS_{A}}(t) + (1-\beta)E_{xH_{A}}(t)].(1-G_{pR_{A}}(t)).$$  \hspace{1cm} (1)

$$G_{sS_{A}}(t) = [\phi G_{nE_{A}}(t) + (1-\phi)Bd_{A}(t)].(1-P_{gN_{A}}(t)).$$  \hspace{1cm} (2)

$$G_{lS_{A}}(t+\Delta t) = G_{lS_{A}}(t) + \varphi.(G_{sS_{A}}(t)-G_{lS_{A}}(t)).(1-$$

$$G_{lS_{A}}(t)).G_{lS_{A}}(t)].\Delta t.$$  \hspace{1cm} (3)

Coping skills (problem-focused coping ($P_{fC}$), and emotional-focused coping ($E_{fC}$)) are influenced by burden and caregiver personality ($G_{pP}$). Note that if a person experiences a very high level burden will have the effect that the possibility for him to choose problem-focused coping becomes smaller and it is a contrary condition for emotional focused coping.

$$P_{fC_{A}}(t) = G_{pP_{A}}(t).(1-Bd_{A}(t)).$$  \hspace{1cm} (4)

$$E_{fC_{A}}(t) = (1-G_{pP_{A}}(t)).Bd_{A}(t).$$  \hspace{1cm} (5)

Positive relationship focused coping ($R_{fC}^+$) depends on the relation between problem focused coping and caregiver’s empathy ($G_{E}$). A high empathy will increase this function, while reducing its counterpart (negative relationship focused coping ($R_{fC}^-$)). Other important state is a condition where either caregiver meets the need of caregiving outcome (bonadaptation) or otherwise (maladaptation). Bonadaptation ($B_n$) is related to the high personal accomplishment (expected personal gain ($P_{gN}$)), and provided support ($S_{cP}$). Maladaptation ($M_d$) is linked to the development of short-term exhaustion ($E_{sH}$), while expected personal gain will reduce this effect.

$$R_{fC_{A}}^+ = P_{fC_{A}}(t).G_{E_{A}}(t).$$  \hspace{1cm} (6)

$$R_{fC_{A}}^- = E_{fC_{A}}(t).(1-G_{E_{A}}(t)).$$  \hspace{1cm} (7)

$$M_d_{A}(t) = [Y.R_{fC_{A}}^+(t)+(1-Y).E_{fC_{A}}(t)].(1-R_{fC_{A}}^+(t)).$$  \hspace{1cm} (8)

$$B_n_{A}(t) = [\rho.R_{fC_{A}}^+(t)+(1-\rho).P_{fC_{A}}(t)].(1-R_{fC_{A}}^-).$$  \hspace{1cm} (9)

$$E_{sH_{A}}(t) = M_d_{A}(t).(1-P_{gN_{A}}(t)).$$  \hspace{1cm} (10)

Experienced personal gain ($E_{pN}$) can be measured by comparing the level of provided support, and the effect of that support towards well-being of the care recipient. Finally, consistent exposure of short-term exhaustion will increase the level of long-term emotional exhaustion.

$$E_{pN_{A}}(t+\Delta t) = E_{pN_{A}}(t) + \vartheta.[(P_{os} ((S_{cP_{A}}(t)-G_{pS_{A}}(t))-$$

$$E_{pN_{A}}(t)].(1-$$

$$E_{pN_{A}}(t))].P_{os}((S_{cP_{A}}(t)-G_{pS_{A}}(t))-$$

$$E_{pN_{A}}(t)].E_{pN_{A}}(t)].\Delta t.$$  \hspace{1cm} (11)
\[ \text{ExH}_A(t+\Delta t) = \text{ExH}_A(t) + \gamma \left[ \text{Pos}(E_{sH_A}(t) - \text{ExH}_A(t)) \right] \cdot (1 - \text{ExH}_A(t)) \cdot \Delta t. \]  

Parameters \( \phi, \beta, \gamma, \) and \( \rho \) provide a proportional contribution factor in all respective instantaneous specifications. Furthermore, the rate of change for all temporal specifications are determined by flexibility rates, \( \gamma, \beta, \phi, \) and \( \psi, \) respectively.

### 9.3 The Integrative Ambient Agent Model

After the discussion of the domain model, this section focuses on the integrative ambient agent model used to support caregivers. A basic element in the ambient agent model is the integration of the domain model within it. By incorporating the domain model, an ambient agent gets an understanding of the processes of its environment [1], [2]. Basically, there are two different ways to integrate a domain model within agent model [4]. First, the domain model is used as a basis to perform analysis of the human’s states and processes by reasoning about observations and specific sensors (analysis model). Second, the domain model is used as a foundation to provide support for the human (support model). These two models are used within the two corresponding components within the ambient agent model. Fig. 9.2 (dotted arrows, left hand side) shows these two types of integration of the domain model in the ambient agent model. A third way of using the domain model is to simulate human behaviour in order to test the ambient agent model (dotted arrow in Fig. 9.2, right hand side).

Fig. 9.2. The integration of a domain model within an agent model
In Fig. 9.2, the solid arrows indicate information exchange between processes. In the ambient agent model, another component is introduced, namely a support action repository. This additional component keeps track of the generated support actions given by the ambient agent to the caregiver. Note that there are two incoming arrows into the analysis component. The first arrow provides information about the environment (care recipient stress, personality and resources), the second arrow provides information about already provided support to the caregiver (from the support action repository). The outcome of the analysis component has the form of assessments, and is used as input for the support component, another incoming arrow for the support component provides the already selected support actions and their frequency from the support action repository. The outgoing arrows from the support component define provided support actions to the caregiver and the support action repository. The support action repository will update the frequency of provided support action from this information. In the next section, the details of the analysis and support component will be discussed.

9.3.1 The Analysis Component

First the analysis component is addresses; see Fig. 9.3. To be able to analyse the dynamics of the caregiver’s and care-recipient’s conditions, an ambient agent should be equipped with a domain model such as the one introduced in Section 9.2. Based on this knowledge, the ambient agent is able to have some understanding of the human processes and actions. Hence, the model for analysis in should in principle include approximately the equivalent concepts as in the domain model. Note that not all concepts that exist in the domain model can be physically observed by the ambient agent [4]. For example, the level of ‘experienced personal gain’ is not something that is explicitly observable in the real world.

To overcome this issue, the agent approximates values for such non-physically observable variables by using beliefs derived using the integrated domain model. To capture important essences in analyzing caregivers’ states, the following concepts are needed: (1) observations of primary stressors, caregiver personality and personal resources, (2) beliefs in (problem and emotional focused) coping characteristics, (3) beliefs in emotional exhaustion (short and long term), (4) beliefs in burden, (5) beliefs in experienced and expected personal gain, (6) beliefs in stress (short and long term), and (7) beliefs in social support. As can be seen, these concepts are similar to the concepts explained in Section 9.2, but as a form of integration embedded in observations or beliefs. For example, the concept of belief about an value V at time t for the variable of the domain model named long_term_stress is named belief(long_term_stress, V, t) in the analysis component. Using these embeddings of
domain concepts, the ambient agent model is able to assess a caregiver’s conditions and provide this information as inputs to the support component, using dynamical relations between such beliefs based on the corresponding dynamical relations in the domain model. For example, suppose in the domain model the following relation is given specifying how state variable $y$ depends on state variables $x_1, x_2, x_3$:

$$y(t + \Delta t) = y(t) + f(x_1(t), x_2(t), x_3(t)) \Delta t$$

Then this is integrated in the analysis model as:

$$\text{belief}(x_1, V_1, t) \land \text{belief}(x_1, V_2, t) \land \text{belief}(x_3, V_3, t) \rightarrow \text{belief}(y, f(V_1, V_2, V_3), t + \Delta t)$$

where $\rightarrow$ denotes a temporal causal relation. Fig. 9.3 provides an overview of such dynamical relations in the analysis model. Note that for simplicity of notation here the values of the states are not mentioned.

![Fig. 9.3. Overview of the Analysis Model for the Caregiving Processes](image-url)
9.3.2 The Support Component

The support model (see Fig. 9.4) can be specified in two different manners. First, the ambient agent can select support based on a rule-based approach using the following representation:

\[
\text{assessment}(x_1, V_1) \land V_1 > \text{threshold}_{\text{assessment}}_1 \land \\
\ldots \land \\
\text{assessment}(x_k, V_k) \land V_k > \text{threshold}_{\text{assessment}}_k \land \\
f\text{frequency}_\text{provided}_\text{support}_A < \text{threshold}_{\text{frequency}_\text{support}}_A
\rightarrow \text{support}_\text{action}(a_1)
\]

Here \(x_1, \ldots, x_k\) represent the assessed conditions, \(V_1, \ldots, V_k\) represent observed or estimated values, and \(a_i\) represents a support action.

![Support model diagram]

**Fig. 9.4.** Overview of the Support Model for a Caregiver

From this representation, the ambient agent will activate support that matches the conditions expressed in the antecedents. Note that all threshold values can be specified by a user. The frequency of provided support can be obtained from the action repository and aims to discontinue from providing a specific support if the caregiver shows no improvement after previously receiving the same support. It provides a mechanism to diversify support provided by an ambient agent.
Another approach to specify a support model is in a numerical manner, using the weighted networks. For this approach, each support action (e.g., \(a_i\)) will receive a summation of weighted input \(y\) from a set of selected assessments \(x_i\). For this, a continuous logistic function can be used, as in [14].

\[
y(t) = \sum_i x_i \cdot w_i
g(t) = \left(\frac{1}{1 + e^{-\sigma(y(t) - \tau)}} - \frac{1}{1 + e^{\sigma\tau}}\right) \cdot (1 + e^{-\sigma\tau})
\]

(13)  (14)

where \(w\) is a weight vector, \(\sigma\) is a steepness and \(\tau\) a threshold parameter. In this choice, a common practice is followed (logistic function) but other types of combination functions can be specified as well. For this approach, the connection between the agent’s assessment results and support actions can be represented as follows:

\[
\text{assessment}(x_1, V_1) \land ... \land \text{assessment}(x_k, V_k) \rightarrow \text{support_action}(a_1, f(V_1, ..., V_k))
\]

where \(f(\ldots)\) represents a combination function.

Results from the continuous logistic function will be evaluated, where a support action with the highest value will be chosen. However, to allow flexibility in providing support, users could choose more support actions with the second or third highest values. The details of the support component can be found in Section 9.4. Fig. 9.4 shows the relationship between results from the analysis component (assessments) and support actions.

9.4 Concepts and Effects in Support for Informal Caregivers

This section explains how the proposed model incorporates characteristics of effective treatments for family caregivers in general and those specific to caregivers of depressed people. By specifying these characteristics of effective treatments for caregivers, the proposed model should be as effective as possible to current standards and knowledge.

9.4.1 Important Concepts in a Support Model

Zarit and Femia [15] describe four characteristics of effective treatments for caregivers: a psychological approach, multidimensionality, flexibility and sufficiency. The psychological approach refers to practicing new skills and behaviours by caregivers in a group or one-to-one interventions with a psychotherapist. Multidimensional interventions are interventions that address multiple stressors and risk factors that affect the caregiver, instead of just one stressor or risk factor. Flexibility means that an effective treatment is flexible in its set up: it should not be a scripted protocol intervention, but the
intervention should be adjustable to the needs of the caregiver [11]. Sufficiency can refer to provision of ongoing support to caregivers, for example, by ongoing support groups, follow-up sessions of an intervention. These four characteristics have been integrated in the proposed support model for family caregivers of depressed people as follows:

The psychological approach can be found in the indirect referral to support groups by the ambient agent and in the direct support actions of ‘reinforce problem focused coping’, ‘realistic expectations’ and ‘increase personal resources caregiver’. The supportive actions are set up in a way that the caregiver is instructed, how to apply general theories to his/her own specific situation and motivated to make plans how to implement these new skills. The ambient agent also gives the caregiver feedback on how he/she is implementing the new skills. The proposed model is also multidimensional, in that it focuses on many possible stressors and risk factors of the caregiver (personality, finances, coping skills, thinking skills, own health). Flexibility in the proposed model can be found in the continuous monitoring of the caregiver by the ambient agent and therefore continuous adjustment of the intervention to the needs of the caregiver. Finally, sufficiency is also integrated in the proposed model by providing ongoing support to the caregiver.

Sufficiency and flexibility are the main advantages of the proposed model. The multidimensionality and psychological approach are still open for improvement, by new insights from research.

Next, it is explained how characteristics of treatments, specially, for caregivers of depressed people were integrated into the proposed model. Cuijpers [7] describes an intervention specific for family caregivers of depressed people, based on his experience with depressed patients and with their family caregivers. There are eight ways for caregivers to deal with the depressed person they care for, which are shown (translated from Dutch) in Fig. 9.5.

<p>| | |</p>
<table>
<thead>
<tr>
<th></th>
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</thead>
<tbody>
<tr>
<td>1.</td>
<td>Gather information</td>
</tr>
<tr>
<td>2.</td>
<td>Do not try to cure the depression.</td>
</tr>
<tr>
<td>4.</td>
<td>Communicate better</td>
</tr>
<tr>
<td>5.</td>
<td>Don’t give too much criticism, do not get too involved.</td>
</tr>
<tr>
<td>6.</td>
<td>Take good care of yourself</td>
</tr>
<tr>
<td>7.</td>
<td>Watch relapse signs after recovery.</td>
</tr>
<tr>
<td>8.</td>
<td>Watch out for suicidal signs.</td>
</tr>
</tbody>
</table>

**Fig. 9.5.** Eight steps in the intervention of family caregivers of depressed people
These eight steps are integrated in the proposed model, as well as the seven ways as Cuijpers describes to relieve the burden or stress experienced by the caregiver, shown in Fig. 9.6, (translated from Dutch) [6].

<p>| | |</p>
<table>
<thead>
<tr>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>1.</td>
<td>Dealing with your emotions/feelings,</td>
</tr>
<tr>
<td>2.</td>
<td>Take good care of yourself,</td>
</tr>
<tr>
<td>3.</td>
<td>Learn to think different,</td>
</tr>
<tr>
<td>4.</td>
<td>Learn to relax,</td>
</tr>
<tr>
<td>5.</td>
<td>Make a good time planning</td>
</tr>
<tr>
<td>6.</td>
<td>Change your social interaction with the depressed person</td>
</tr>
<tr>
<td>7.</td>
<td>Be assertive</td>
</tr>
</tbody>
</table>

Fig. 9.6. Seven ways to relieve the burden or stress experienced by the caregiver

The current support model consists of multiple supportive actions advised by the ambient agent to the caregiver. The first support action is called “increase personal resources caregiver”. This support action is aimed at teaching the caregiver to manage stress, which will decrease the burden. Examples are teaching the caregiver to make a to-do list and becoming more assertive, like in points 5 and 7 in Fig. 9.5. This will affect the caregiver’s personality (as in changing his/her stress reactions: now he/she gets well organised, and more assertive) and the caregiver’s social and financial resources (as in getting financial/practical help from friends/family).

The second support action is called “reinforce problem focused coping caregiver”. Here the ambient agent teaches the caregiver how to learn to apply problem focused coping instead of emotion focused coping and gives feedback. Research shows that coping is a learnt behaviour, see a review in: [13]. Examples are: text messages or instruction movies on phone/through emails, in which it is shown how to deal in certain situations or dialogues with the depressed person. Also the ambient agent will ask to plan and report the new skills the caregiver has to apply, so it can monitor the newly developed skills and give feedback to the caregiver. This support action decreases the caregiver’s emotion focused coping and increases the caregiver’s problem focused coping: increases. These skills fall under points 2-5 in Fig. 9.5 and 1,3,6,7 in Fig. 9.6.

The third and fourth support actions are called “realistic expectations and self-care caregiver”. In these actions, the ambient agent gives information about the illness so the caregiver gets an understanding of the behavioural patterns and needs of the depressed person (corresponding to point 1, Fig. 9.5). Also the ambient agent teaches the caregiver to take care of him/herself (physically, emotionally, and mentally) and asks for reports and plans and gives feedback (points 6 Fig. 9.5, points 2, 4, Fig. 9.6). Examples are: text messages or movies
on phone/through emails, in which examples of the behaviours of other depressed persons are given, like how fast they recover or relapse. Giving tips in self-care, like taking a time-out, finding social support, eating healthy, exercising regularly and learning relaxation exercises. These support actions increase the caregiver’s experienced personal gain, because the caregiver will experience less disappointments since the caregiver learns to have more realistic expectations towards the depressed person [10]. The caregiver’s short term emotion exhaustion will also decrease.

The fifth support action is aimed at other persons than the ‘main’ informal caregiver, namely other (possible) caregivers, friends of the ‘main’ caregiver, or a specialist like a doctor or therapist. The fifth support action is called: “giving warning” and refers to the ambient agent giving information to another person than the caregiver it is supporting. This information contains a warning signal that the depressed person and the caregiver both need support from others. The effect of support from an ambient agent to the caregiver will be dealt in the next section.

9.4.2 Dynamics Specifications of the Effects from a Support Model

Using the support concepts introduced in the previous sections, it is possible to specify computational properties to visualize the effects from the support provided by a support agent. The dynamic specifications of an agent-based support can be structured pertinent to the purposes of the support, namely; (1) to reduce long-term exhaustion in a caregiving process, (2) to develop problem-focused coping skills, and (3) to improve personality attributes that reduce the physiological signs of stress [6][8][13]. The asterisk sign (*) is used to represent the extended equations about the effect of the supports towards a caregiver’s processes.

Support to reduce long-term emotional exhaustion. In this case, the support agent aims to reduce further negative influences that cause emotional exhaustion. From Table 9.1, the support agent will provide important advices and suggestions to regulate self-care ($Sc$), to increase external personal resources ($Ep$), and to foster more realistic expectations. The effect of short-term emotional exhaustion ($EsH$) after following agent’s support is estimated after adding a new support parameter, $\delta_{SA}$ and a self-care effect into the original equation (Equation (10)). This indicates that when self-care, $Sc(t) \rightarrow 1$ and $\delta_{SA} \rightarrow 1$, then the short-term emotional exhaustion is recuced to zero. Another important effect after following the support is having more external personal resources. Thus, a new caregiver personal resource ($GgR^*$) can be
expressed as having a combination of existing resources \((G_{pR})\) and external resources \((E_p)\).

\[
\begin{align*}
E_{xH^*A}(t) &= Md_A(t). (1 - PgN_A(t)). (1 - \delta_{SA}. Sc(t)) \\
G_{gR^*A}(t) &= \delta_{EA} . G_{pR_A}(t) + (1 - \delta_{EA}). E_p(t)
\end{align*}
\]  

(15)  

(16)

The new value of experienced personal gain \((E_{pN})\) depends on a combination of the previous equation in (11) and a support contribution when a person is capable to achieve realistic expectations \((Re)\).

\[
\begin{align*}
E_{pN^*A}(t+\Delta t) = &E_{pN_A}(t) + \vartheta \cdot (\delta_{RA} \cdot \left[ (Pos ((Scp_A(t) - G_{pSA(t)}) - E_{pN_A(t)})(1 - E_{pN_A(t)})) - Pos(- ((Scp_A(t) - G_{pSA(t)}) - E_{pN_A(t)})E_{pN_A(t)}) \right] + (1 - \delta_{RA}). Re(t). (1 - E_{pN_A(t)})\Delta t.
\end{align*}
\]  

(17)

**Support to reduce dependency on emotional-focused coping skills:** In order to visualize the effect when a person follows agent’s advices to reinforce problem-focused skills, both new problem-focused \((PfC)\) and emotional-focused coping \((EfC)\) skills are calculated as follows:

\[
\begin{align*}
PfC^*A(t) &= G_{pP_A}(t). (1 - ((1 - \delta_{FA}. Rp(t)). Bd_A(t))) \\
EfC^*A(t) &= (1 - G_{pP_A}(t)). Bd_A(t). (1 - \delta_{FA}. Rp(t)).
\end{align*}
\]  

(18)  

(19)

where \(\delta_{FA}\) determines the influence of the acceptance in change coping skills and \(Rp\) represents reinforce problem focused coping skills. \(Bd\) represents burden and \(G_{pP}\) represents the caregiver personality.

**Support to reduce physiological signs of stress:** For this type of support, changes in both the caregiver personality and resources are needed. In this case, a new caregiver personality \((G_{pP^*})\) is calculated by combining the existing personality, and the positive personality \((Cp)\) from the support. Equation (14) provides similar effect for the new caregiver resources.

\[
G_{pP^*A}(t) = \delta_{PA} \cdot G_{pP_A}(t) + (1 - \delta_{PA}). Cp(t)
\]  

(20)

In addition to this, \(\delta_{EA}\), \(\delta_{RA}\) and \(\delta_{PA}\) are support-acceptance parameters; it represents a person’s ability to accept respective changes from the support.

9.5 Simulation Results

The ambient agent model presented in Section 9.3, integrating the domain model as described in Section 9.2 was implemented in Matlab in order to
perform simulation experiments. For the simulations, the functioning of the designed system was explored in interaction with three fictional types of caregivers (caregiver 1 (CG1), caregiver 2 (CG2), and caregiver 3 (CG3)). Both caregivers (1 and 2) are ineffective caregivers and susceptible for long-term stress in a caregiving process (low in positive personality and resources), while caregiver 3 is an effective caregiver. In this case, caregiver 1 ignores the support provided by the intelligent support agent, and caregiver 2 follows the support. In addition to this, information about the care-recipient’s (CR) stress buffer and long-term stress has been used to measure the outcome of the agent support (as in [2]). The care-recipient stress buffer represents a process of support protecting the care recipient from potentially adverse effects of stressful events (stressors). Therefore, many studies have shown that a high stress-buffer level will reduce the development of care recipient long-term stress level in future [6][9]. In this simulation, the care recipient is experiencing negative events (stressors) and expects supports from a caregiver (also facing incoming stressors).

**Table 9.1 Initial Values for the Simulation Experiments**

<table>
<thead>
<tr>
<th></th>
<th>Caregiver 1 (CG1)</th>
<th>Caregiver 2 (CG2)</th>
<th>Caregiver 3 (CG3)</th>
<th>Care recipient (CR)</th>
</tr>
</thead>
<tbody>
<tr>
<td>CG personality</td>
<td>0.2</td>
<td>0.1</td>
<td>0.8</td>
<td>-</td>
</tr>
<tr>
<td>CG personal resources</td>
<td>0.2</td>
<td>0.1</td>
<td>0.7</td>
<td>-</td>
</tr>
<tr>
<td>CG empathy</td>
<td>0.3</td>
<td>0.3</td>
<td>0.7</td>
<td>-</td>
</tr>
<tr>
<td>CR personality</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>0.3</td>
</tr>
<tr>
<td>CR coping skills</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>0.1</td>
</tr>
</tbody>
</table>

These conditions are chosen to show the effect of different effects on the long-term stress, emotional exhaustion, provided support, and on the influences of the support. In addition to this, there are several parameters that can be varied to simulate different characteristics. However, in this simulation, we used the following settings: $t_{\text{max}} = 1000$ (to represent a monitoring activity up to 42 days), $\Delta t = 0.3$, regulatory rates = 0.5, flexibility rates = 0.2, and support-acceptance rates = 0.3. These settings were obtained from several experiments to determine the most suitable parameter values for the model. In addition, the weighted network is implemented in the support model to select the most appropriate support. To illustrate the effect of support, all caregivers receive support by the agent after half of the simulation period.

Fig. 9.7 visualizes a condition when the caregiver is avoiding the agent’s support while facing intense stressors. Facing such events, both persons (CG1 and CR) are facing high long-term stress levels and emotional exhaustion in the long run. As a result, the caregiver is experiencing a low personal gain and support provision, which later lower the effect of stress buffering in care.
recipient. This condition occurs when a caregiver feel burden by the caregiving activities [12]. Eventually, without any support, both caregiver and care recipient will have a higher possibility to get depressed.

![Graph showing emotional exhaustion and personal gain](image1)

![Graph showing stress buffering and LT stress](image2)

**Fig. 9.7.** An ineffective caregiver (CG1) without support, and a bad care recipient (CR)

However, in Fig. 9.8 different scenarios can be seen when an ineffective caregiver does follow the provided support from a support agent. After following the recommended advices, the caregiver improves his / her ability to provide support. One of the precursors to explain this outcome is the increasing caregiver’s personal gain. It is consistent with the findings that suggest that caregiving satisfaction encourages a caregiver to provide more support [10][12]. In addition to this, by following the specific advices, the caregiver is helped to apply more focused-coping skills, which later on influence the development of positive relationship focused coping. In many reports in the literature, problem-focused coping skills give a positive outcome in a caregiving process, for both caregiver and care recipient.

In another case (see Fig. 9.9), an effective caregiver requires no support from the support agent since he / she is capable to provide adequate support during the caregiving process. It is obvious to see that caregivers with more positive personality, personal resources and empathy tend to provide better support compare to those who are not [11][13]. This results in an increase of the stress buffering level, and later will dampen the development of the caregiver’s long-term stress. Another interesting pattern to see is when the caregiver is experiencing repeated stressors (oscillating condition). In this case, caregiver CG1 shows monotonic increasing in his / her long-term stress. In contrary,
caregiver CG2 experiences monotonic decreasing in his/her long-term stress. Similar condition also occurs in caregiver CG3 but decreases much faster and with lower oscillation compared to the condition in CG2.

Fig. 9.8. An ineffective caregiver (CG2) with support, and a bad care recipient (CR)

Fig. 9.9. An effective caregiver (CG3) without support, and a bad care recipient (CR)
9.6 Verification of the Simulation Results

In order to verify whether the model indeed generates results that adhere to psychological theories, a set of properties have been identified from related literatures. These properties have been specified in a language called Temporal Trace Language (TTL). TTL is built on atoms referring to states of the world, time points, and traces. This relationship can be presented as \( \text{holds}(\text{state}(\gamma, t), p) \) or \( \text{state}(\gamma, t) \models p \), which means that state property \( p \) is true in the state of trace \( \gamma \) at time point \( t \) \[5\]. It is also comparable to the \textit{Holds}-predicate in Situation Calculus. Based on that concept, dynamic properties can be formulated using a hybrid sorted predicate logic approach, by using quantifiers over time and traces and first-order logical connectives such as \( \neg, \land, \lor, \Rightarrow, \forall \), and \( \exists \). A number of simulations including the ones described in Section 9.4 have been used as basis for the verification of the identified properties and were confirmed. Note that \( tb \) and \( te \) are the initial and final time points of the simulation period.

**VP1: Monotonic decrease of long-term stress**

For all time points \( t_1 \) and \( t_2 \) between \( tb \) and \( te \) in trace \( \gamma_1 \) if at \( t_1 \) the value of the caregiver’s long-term stress is \( R_1 \) and at \( t_2 \) the value of the caregiver’s long-term stress is \( R_2 \) and \( t_1 < t_2 \), then \( R_1 \geq R_2 \)

\[
\forall \gamma: \text{TRACE}, \forall R_1, R_2: \text{REAL}, t_1, t_2: \text{TIME} \quad \text{state}(\gamma, t_1) \models \text{long_term_stress}(cg, R_1) \& \text{state}(\gamma, t_2) \models \text{long_term_stress}(cg, R_2) \& tb \leq t_1 \leq te \& tb \leq t_2 \leq te \& t_1 < t_2 \Rightarrow R_1 \geq R_2
\]

By checking property VP1, one can verify whether a caregiver’s long term stress decreases monotonically over a certain time interval. For example, the caregiver’s long-term stress turned out to decrease over the second half of the trace for caregivers that have received and accepted the provided support or for an effective caregiver.

**VP2: Decrement of a caregiver’s long-term stress below a certain level \( x \)**

A time point \( t \) exists such that for all \( t_1 > t \) the value of long-term stress is at most level \( x \).

\[
\forall \gamma: \text{TRACE}, \exists t: \text{REAL} [tb < t < te \& \forall t1: \text{TIME} \geq t [t \leq t_1 \leq te \& \text{state}(\gamma, t_1) \models \text{long_term_stress}(cg, R_1) \Rightarrow R_1 \leq x]
\]

Property VP2 can be used to verify whether a variable eventually approaches some (given) value. In the experiments reported here, \( x = 0.3 \) was used as a borderline value for long-term stress to assume a caregiver is effective to provide social support. In many cases, after following the advices, the caregiver will reach this borderline value. A number of more specific other properties have been identified and verified, such as the following ones, which compare
cases with a specific type of support and cases without. Note that formalisation of such comparison properties makes use of the possibility to explicitly refer to traces in the language TTL; this is not possible in the usual temporal logical languages.

**VP3: Effect of problem coping skills on a caregiver’s long-term stress**

After a caregiver has followed the programme to improve problem focused coping skills for some time, the long-term stress level is more reduced than for a caregiver who does not.

\[ \forall \gamma_1, \gamma_2: \text{TRACE}, \forall R_1, R_2: \text{REAL}, t_1, t_2: \text{TIME} \]

\[ \text{state}(\gamma_1, t_1) \models \text{support_problem_coping} \land \text{state}(\gamma_2, t_1) \models \text{not support_problem_coping} \land \\
\text{state}(\gamma_1, t_2) \models \text{long_term_stress}(cg, R_1) \land \text{state}(\gamma_2, t_2) \models \text{long_term_stress}(cg, R_2) \land \\
t_1 < t_2 \Rightarrow R_1 < R_2 \]

**VP4: Effect of realistic expectation on emotional exhaustion**

After a caregiver has followed the support programme to reduce unrealistic expectation, the long-term emotional exhaustion is more reduced than for a caregiver who does not.

\[ \forall \gamma_1, \gamma_2: \text{TRACE}, \forall R_1, R_2: \text{REAL}, t_1, t_2: \text{TIME} \]

\[ \text{state}(\gamma_1, t_1) \models \text{support_realistic_expectation} \land \text{state}(\gamma_2, t_1) \models \text{not support_realistic_expectation} \land \\
\text{state}(\gamma_1, t_2) \models \text{long_term_emotional_exhaustion}(cg, R_1) \land \text{state}(\gamma_2, t_2) \models \text{long_term_emotional_exhaustion}(cg, R_2) \land \\
t_1 < t_2 \Rightarrow R_1 < R_2 \]

**VP5: Effectiveness of support on provided support to the care recipient**

A caregiver who follows the suggested support by an agent will provide better support to the care recipient than a caregiver who does not.

\[ \forall \gamma_1, \gamma_2: \text{TRACE}, \forall R_1, R_2, d: \text{REAL}, t_1, t_2: \text{TIME} \]

\[ [[[\text{state}(\gamma_1, t_1) \models \text{support_realistic_expectation} \land \text{state}(\gamma_1, t_1) \models \text{support_problem_coping} \land \\
\text{state}(\gamma_1, t_1) \models \text{support_add_personal_resources}] \land \text{state}(\gamma_2, t_1) \models \text{not support_realistic_expectation} \land \text{state}(\gamma_2, t_1) \models \text{not support_problem_coping} \land \\
\text{state}(\gamma_2, t_1) \models \text{not support_add_personal_resources}] \land \\
\text{state}(\gamma_1, t_2) \models \text{long_term_stress}(cg, R_1) \land \text{state}(\gamma_2, t_2) \models \text{long_term_stress}(cg, R_2) \land \\
t_1 < t_2 \Rightarrow R_1 < R_2] \]

9.7 Discussion

In this chapter, an ambient agent model was proposed that supports caregivers for depressed persons and promote their well-being. Caring for a depressed person may entail a serious risk for the health of the caregiver. The designed
ambient agent integrates a domain model of the functioning of the caregiver and the care recipient and their interaction, adopted from [3]. It exploits model-based reasoning to monitor and assess the caregiver’s state using this computational model. Based on these assessments dedicated support actions are generated that are tuned to the circumstances, thereby taking into account guidelines adopted from [7].

Although some applications have been designed to support persons with a depression (e.g., [2]), automated support for caregivers has not been addressed, as far as the authors know. The model introduced here was evaluated by conducting a number of simulation experiments for different scenarios and types of caregivers, and formal verification of the outcomes of these experiments. These outcomes show that using the advices provided by the ambient agent results in improvement in the situation in comparison to not using such advices; for verification of this type of comparison properties (which are not representable in the often used temporal languages; see also [5]) the language TTL and its software environment [5] has proved its usefulness.

References


Chapter 10 - An Agent-Based Model for Integrated Contagion and Regulation of Negative Mood

Azizi Ab Aziz, Jan Treur, C. Natalie van der Wal

Abstract. Through social interaction, the mood of a person can affect the mood of others. The speed and intensity of such mood contagion can differ, depending on the persons and the type and intensity of their interactions. Especially in close relationships the negative mood of a depressed person can have a serious impact on the moods of the ones close to him or her. For short time durations, contagion may be the main factor determining the mood of a person; however, for longer time durations individuals also apply regulation mechanisms to compensate for too strong deviations of their mood. Computational contagion models usually do not take into account such regulation. This chapter introduces an agent-based model that simulates the spread of negative mood amongst a group of agents in a social network, but at the same time integrates elements from Gross’ emotion regulation theory, as the individuals’ efforts to avoid a negative mood. Simulation experiments under different group settings pointed out that the model is able to produce realistic results, that explain negative mood contagion and emotion regulation behaviours posed in the literature.

This Chapter appeared as:
10.1 Introduction

There is a wide consensus in sociological literature that human mood spreads through social networks [9, 11]. This social phenomenon is known as contagion. Especially negative moods are strongly influenced by social contacts (e.g., family, friends, colleagues, and neighbours), for example, when the social interaction involves conflict issues or stressful events [4, 15]. Agent-based computational models for contagion of different types of mental states can be found, for example, in [1, 10]. However, in addition to contagion at the social level, also emotion regulation within individuals plays an important role [3]. Emotion regulation is a process through which individuals balance their emotions by exerting forms of control on how they feel [8]. For instance, by avoiding situations or persons who trigger negative emotions, or suppressing anger when receiving bad comments from interviewers. By such emotion regulation mechanisms, persons have the ability to suppress negative influences from interaction with others and maintain a form of emotional homeostasis [7, 8]. For example, if a partner of a depressed person has regulation mechanisms that are strong enough, he or she does not need to become depressed, but if the mechanisms are less strong, there is a serious risk that the partner also becomes depressed.

In recent years researchers have focused on understanding the mechanisms of emotion regulation, and social contagion separately [2, 13, 15]. However, little information is available to explain how these processes work in an integrated manner by means of computational models. In this chapter, an agent-based model is proposed that formalizes and simulates the integrated contagion and regulation of negative mood. In order to exemplify the proposed model, simulation experiments have been performed with a variety of scenarios that include varying personal characteristics and group or network compositions. Attributes were configured, to represent the personality and social characteristics of different individuals. Simulation traces were generated, to show behaviour of these individuals over time, under multiple conditions.

10.2 Mood Contagion and Regulation

In this section, important ideas and concepts in negative mood contagion and emotion regulation research are addressed. These ideas form the basis of the current computational model that will be formally described in the next section. As described in [5], the degree of mood contagion in groups is influenced by the valence and energy of the mood. One of the fundamental components in mood contagion is the contagion strength between individuals within a group [6]. It involves the type of interaction between individuals (channel strength from sender to receiver) and personality characteristics of the
sender (*expressiveness*) and receiver (*openness*). For negative mood contagion, channel strength can be defined as the intensity of the social interaction, either via *physical contact* (i.e., face-to-face), or *virtual interaction* (i.e., text message, social networking) [16]. Neighbourhood and personality characteristics, affect the openness for mood contagion of a person [11, 12]. For example, a neurotic individual tends to aggravate negative perception towards incoming mood [14]. In addition to this, a bad neighbourhood (physical or social) also creates a negative influence towards individual’s perception in social interaction [12]. Expressiveness is related to the ability of an individual to induce contagion, where an extravert individual can induce a stronger contagion of a negative mood than an introvert individual, because an extravert person expresses his or her internal feelings stronger than an introvert person [1].

Besides mood contagion, emotion regulation plays a role in the experience and transfer of moods. It is important to understand the emotion regulation process, by knowing which different strategies individuals use to exert control over their moods [2]. To serve this purpose, Gross’ emotion regulation theory provides a number of strategies to affect individuals’ level of emotion [7]. This theory differentiates these strategies into *antecedent-focused strategies* and *response-focused strategies*. The former type of strategies refer to the process preparing for response tendencies before they are (fully) activated, and the latter deal with the actual activation or suppression of the expression of emotional responses [13]. Antecedent-focused strategies can involve the external situation of the person (e.g., avoiding certain places or persons), or the internal processes (e.g., redirecting attention or cognitive interpretation). Gross [7, 8] mentions four examples of antecedent-focused strategies: *situation selection, situation modification, attentional deployment, and cognitive change*. In a response-focused strategy, response modulation is used (e.g., suppressing expressing of negative emotions, or amplifying expression of positive emotions).

Situation selection involves selecting a situation that supports the individual’s emotional well-being. This may involve physical and/or social aspects. For example, if a person has a bad response on low light intensity, a form of regulation is to increase this intensity. Especially relevant to the integration with social contagion processes, is the regulation of the social situation. For example, if a person feels bad in a certain social environment, he/she can decrease his/her openness for and intensity of social interaction. Situation modification is similar to selection, but addresses only some aspects of a situation. Attentional deployment includes redirection of attention, for example, on more neutral or positive elements [7]. Cognitive change refers to change in how an individual interprets the situation. Response modulation refers to physical or behavioural actions that decrease the expression of negative emotions [8].
10.3 The Agent-Based Model

The agent-based model introduced in this section combines knowledge on mechanisms for mood contagion and emotion regulation, as briefly introduced above. In this computational model these mechanisms are encapsulated, allowing the simulation of how fragile individuals in their social environment are, towards negative mood contagion. The model describes a process to maintain homeostasis for mood. Through social interaction, there is a habitual tendency of an individual to perceive the negative mood of others and to regulate his or her own moods. Both processes are governed by individual’s socio-culture, default (norm) personality, and his or her negative mood. In the formalized model, all nodes are designed to have values ranging from 0 (low) to 1 (high). The interaction will determine the new value for each node, either by a series of accumulations or an instantaneous interaction. To represent these relationships in agent terms, each variable will be coupled with an agent’s name (A or B) and a time variable t. The description of these formalizations is described below. For a global overview, see Fig. 10.1.

10.3.1 Norm Values

Norm values indicate which level each individual is inclined to approximate during the process: an individual tries too keep itself within safe boundaries around these values. These norm values can be seen as a basis for ‘default behavioural patterns’; e.g., the openness a person tends to have, based on neighbourhood characteristics and level of neuroticism, or a default level of expressiveness, based on personality characteristics. These norm values are also the natural initial settings of the persons in scenarios. The norm value $C_{\text{norm}_{AB}}$ at some point in time $t$ for the channel of agent A to agent B, can be related to the amount of physical ($PI_{AB}$) and virtual ($VI_{AB}$) interactions that take place, where 0 means no physical or virtual interaction with others, and 1 means a lot of physical interaction [12]. This interaction is regulated by the proportional parameter $\alpha$. If $\alpha = 0.5$, both types of interactions have the same effect, otherwise, one of these types of interactions has more effect on the channel norm value.

$$C_{\text{norm}_{AB}}(t) = \alpha \cdot PI_{AB}(t) + (1-\alpha) \cdot VI_{AB}(t)$$

Note that the interaction can be bidirectional, so that $C_{\text{norm}_{AB}}(t) = C_{\text{norm}_{BA}}(t)$, but this is not assumed to be always the case; the model also covers asymmetric cases, for example, where frequently text messages are sent from A to B but not conversely, or B follows A on Twitter but not the other way around.

Next, the openness norm value $O_{\text{norm},A}$ of agent A, first relates to the (bad) neighbourhood circumstances of A expressed in a concept $NH_A$, where a
value of 1 means a very ‘bad’ neighbourhood, which makes a person vulnerable to negative mood, and the value 0 means the neighbourhood does not make a person more susceptible to negative mood of others. $NH_A$ is modelled as the product of the social ($SNH_A$) and physical ($PNH_A$) neighbourhood and of the person. If $PNH_A = 1$, then the physical neighbourhood is very ‘bad’, and it will have a negative effect on the person’s susceptibility. By multiplication of the social and physical neighbourhood in (2), a more ‘positive’ social neighbourhood (with a low value), will make the impact of the ‘bad’ physical neighbourhood smaller [12].

$$NH_A(t) = SNH_A(t).PNH_A(t)$$ (2)

The openness norm value $O_{norm,A}$ of agent $A$, combines the concepts of a bad neighbourhood $NH_A$, with the concepts friends ratio $NF_A$ and neuroticism $N_A$. In [12]

Fig. 10.1. Overview of the Agent-Based Model Integrating Mood Contagion and Regulation

it is described that the more friends you have, the less prone you are to negative mood contagion. The quantity $NF_A$ is defined as a number between 0 and 1 (a ‘friend ratio’): the number of friends is divided by a fixed number (serving as an upper bound) to normalise it. For example, if the upper bound taken is 10 (as in the simulations discussed in Section 9.4) then one friend will give $NF_A = 0.1$, whereas 7 friends will give $NF_A = 0.7$. Parameter $\phi$ regulates the equation; so that it can be modelled which concept can have more effect.
on the openness norm value than the other. In addition to this, [11] put forward that the more neurotic you are, the more susceptible you are to negative mood of others. Therefore, the level of neuroticism $N_A$ can amplify or reduce the positive effects of having such as a high number of friends and/or a not bad neighbourhood.

$$O_{norm,A}(t) = [\varphi(1-NF_A(t)) + (1-\varphi)NH_A(t)]N_A(t)$$ (3)

Finally, in the current model, the expressiveness norm value $E_{norm,A}$ of agent $A$ is initialised by a number between 0 and 1, not a formula. The number represents the level of expressiveness a person tends to approximate in daily life, where 0 means low expressiveness and 1, high expressiveness.

10.3.2 The Dynamics of Mood Contagion and Emotional Regulation

In this section the dynamical model for mood contagion and regulation is introduced. A summary of the parameters and state variables of the model is shown in Table 10.1.

For the mechanisms behind mood contagion, elements from the model presented in [1] have been adopted. The main building block of mood contagion in this model is the contagion strength $CS_{AB}$ from agent $A$ to agent $B$, where it represents the type and intensity of the contact between agent $A$ and agent $B$. The higher the value of $CS_{AB}$, the more contagion will take place.

$$CS_{AB}(t) = E_A(t)C_{AB}(t)O_B(t) \quad \text{where } A \neq B$$ (4)

Here, $E_A$ is the personal characteristic expressiveness (the degree in which a person can express his/her mood), $C_{AB}$ the channel strength (intensity of contact, depending on the social relation) from $A$ to $B$, and $O_B$ the openness (the degree of susceptibility) of the receiver $B$. Using this equation, the group contagion strength is computed. The group contagion strength $CS_A*(t)$ towards $A$ is the overall strength by which the negative mood of all other group members is received by $A$:

$$CS_A*(t) = \sum_{B \neq A} CS_{BA}(t)$$ (5)

Note that for the sake of simplicity here a linear (sum) combination is used. Alternatively, also a logarithmic or logistic combination function might be used. Given the mood levels $M_B(t)$ of the agents $B \neq A$ at time $t$, the weighted group impact $M_A*(t)$ of all other agents in the group towards agent $A$ is modelled as:
More details of this model for contagion can be found in [1]. Next the dynamics of the mechanisms for integrated emotion regulation and negative mood contagion are modelled in (7), (8), (9), and (10). The general pattern underlying these dynamical relationships is

\[ Y_A(t+\Delta t) = Y_A(t) + \tau \cdot <\text{change_expression}> \cdot \Delta t \]

Here the change of \( Y \) is specified for a time interval between \( t \) and \( t+\Delta t \); the \( \tau \) are personal flexibility parameters that represent the speed of the cognitive adjustment processes. Within \(<\text{change_expression}>\) two cases are considered: upward (positive) change \(<\text{upward_change}>\), and downward (negative) change \(<\text{downward_change}>\).

\(<\text{change_expression}> = (1-Y_A(t)). <\text{upward_change}> + Y_A(t). <\text{downward_change}>\)

The upward and downward change expressions are determined using the operator Pos(\( x \)) defined as Pos(\( x \)) = \( x \) when \( x \geq 0 \), else 0.

\(<\text{upward change}> = \text{Pos}<\text{basic change}>\)
\(<\text{downward change}> = -\text{Pos}-<\text{basic change}>\)

Within the basic change expression for (7), (8), and (9), two parts are considered. The first part incorporates the emotion regulation, and the second part the maintenance of homeostasis.

\(<\text{basic_change}> = <\text{regulation_change}> + <\text{maintenance_change}>\)

The latter change expressions were taken linear in the deviation:

\(<\text{regulation_change}> = \zeta \cdot [M_{\text{norm}A} - M_A(t)]\)
\(<\text{maintenance_change}> = \upsilon \cdot [Y_{\text{norm}A} - Y_A(t)]\)

Here \( \zeta \) and \( \upsilon \) are more specific flexibility parameters, for regulation and maintenance. Next it is shown how this general pattern was applied for channel strength (7), openness (8), and expressiveness (9). Firstly, the concepts of emotion regulation are represented in the dynamic adjustment of the strength of the channel from agent \( A \) to \( B \). In (7) this occurs by comparing the current mood level to the mood norm value and comparing the current...
channel level with the channel norm value. These possible deviations influence the adjustment in the strength of the channel that the agent makes. This covers situations in which a person is infected by negative mood from other persons and directs his/her attention away, or physically moves to another place.

\[
C_{BA}(t+\Delta t) = C_{BA}(t) + \tau_{CA} \left[ (I - C_{BA}(t)) \cdot \text{Pos}(\zeta_{CA} [M_{normA} \cdot M_{A}(t)] + \nu_{CA} [C_{normBA} - C_{BA}(t)]) - \frac{C_{BA}(t)}{C_{BA}(t)} \cdot \text{Pos}(\zeta_{CA} [M_{normA} \cdot M_{A}(t)] - \nu_{CA} [C_{normBA} - C_{BA}(t)]) \right] \Delta t
\]

The dynamic relation for the openness \(O_A\) of agent \(A\) models another antecedent-focused emotion regulation mechanism [7].

\[
O_{A}(t+\Delta t) = O_{A}(t) + \tau_{OA} \left[ (I - O_{A}(t)) \cdot \text{Pos}(\zeta_{OA} [M_{normA} \cdot M_{A}(t)] + \nu_{OA} [O_{normA} - O_{A}(t)]) - \frac{O_{A}(t)}{O_{A}(t)} \cdot \text{Pos}(\zeta_{OA} [M_{normA} - M_{A}(t)] - \nu_{OA} [O_{normA} - O_{A}(t)]) \right] \Delta t
\]

The expressiveness \(E_{A}\) of agent \(A\) involves a response-based emotion regulation mechanism [7, 8]. In (9), expressiveness is adjusted towards the norm value, but also adjusted to decrease expression of negative mood.

\[
E_{A}(t+\Delta t) = E_{A}(t) + \tau_{EA} \left[ (I - E_{A}(t)) \cdot \text{Pos}(\zeta_{EA} [M_{normA} \cdot M_{A}(t)] + \nu_{EA} [E_{normA} - E_{A}(t)]) - \frac{E_{A}(t)}{E_{A}(t)} \cdot \text{Pos}(\zeta_{EA} [M_{normA} - M_{A}(t)] - \nu_{EA} [E_{normA} - E_{A}(t)]) \right] \Delta t
\]

Finally in (10), an internal antecedent-focused emotion regulation mechanism called re-appraisal [8] is modelled. Here within the generic pattern discussed above the expression \(<\text{basic\_change}>\) is instantiated as follows.

\[
<\text{basic\_change}> = <\text{contagion\_change}> + <\text{reappraisal\_change}>
\]

where

\[
<\text{reappraisal\_change}> = \lambda_{A} [M_{normA} \cdot M_{A}(t)]
\]

\[
<\text{contagion\_change}> = CS_{A} * (t) \cdot \left[ \beta_{A} \cdot (1 - (1 - M_{A}(t)) \cdot (1 - M_{A}(t))) + (1 - \beta_{A}) \cdot M_{A}(t) \cdot M_{A}(t) \right]
\]

The latter expression was adopted from [1]. This provides the following mood dynamics relation:
\[ M_A(t+\Delta t) = M_A(t) + \tau_{M_A}[(1-M_A(t)) \cdot \text{Pos}(CS_A^*(t) \cdot \beta_A \cdot (1-M_A(t)) \cdot (1-M_A^*(t))) + (1-\beta_A) \cdot M_A(t) \cdot M_A^*(t) - \lambda_A [M_{\text{norm}A} \cdot M_A(t)]] - M_A(t) \cdot \text{Pos}(-CS_A^*(t) \cdot \beta_A \cdot (1-M_A(t)) \cdot (1-M_A^*(t))) + \lambda_A [M_{\text{norm}A} \cdot M_A(t)] - M_A(t) \cdot \lambda_A [M_{\text{norm}A} \cdot M_A^*(t)] \cdot \Delta t \]

\[ (1-\beta_A) \cdot M_A(t) \cdot M_A^*(t) - M_A(t) \]  

\[ (1-\beta_A) \cdot M_A(t) \cdot M_A^*(t) - M_A(t) + \lambda_A [M_{\text{norm}A} \cdot M_A^*(t)] \cdot \Delta t \]

Table 10.1. Parameters and state variables of the model

<table>
<thead>
<tr>
<th>Concepts</th>
<th>Formalization</th>
</tr>
</thead>
<tbody>
<tr>
<td>negative mood of agent A</td>
<td>( M_A )</td>
</tr>
<tr>
<td>norm value for the negative mood of agent A</td>
<td>( M_{\text{norm}A} )</td>
</tr>
<tr>
<td>weighted group impact</td>
<td></td>
</tr>
<tr>
<td>expressiveness of agent A (sending side)</td>
<td>( E_A )</td>
</tr>
<tr>
<td>norm value for expressiveness of agent A</td>
<td>( E_{\text{norm}A} )</td>
</tr>
<tr>
<td>channel strength from agent A to agent B</td>
<td>( C_{AB} )</td>
</tr>
<tr>
<td>norm value for channel from agent A to agent B</td>
<td>( C_{\text{norm}AB} )</td>
</tr>
<tr>
<td>contagion strength from agent A to agent B</td>
<td>( CS_{AB} )</td>
</tr>
<tr>
<td>overall group contagion strength towards agent A</td>
<td>( CS_A )</td>
</tr>
<tr>
<td>openness of agent A (receiving side)</td>
<td>( O_A )</td>
</tr>
<tr>
<td>norm value for openness of agent A</td>
<td>( O_{\text{norm}A} )</td>
</tr>
<tr>
<td>physical interaction from A to B (face-to-face)</td>
<td>( PI_{AB} )</td>
</tr>
<tr>
<td>virtual interaction from A to B</td>
<td>( VI_{AB} )</td>
</tr>
<tr>
<td>number of friends ‘friend ratio’ of agent A</td>
<td>( NF_A )</td>
</tr>
<tr>
<td>bad neighbourhood of agent A</td>
<td>( NH_A )</td>
</tr>
<tr>
<td>level of neuroticism of agent A</td>
<td>( N_A )</td>
</tr>
<tr>
<td>bad social neighbourhood of A</td>
<td>( SNH_A )</td>
</tr>
<tr>
<td>bad physical neighbourhood of A</td>
<td>( PNH_A )</td>
</tr>
<tr>
<td>proportional parameter for ( C_{\text{norm}A} )</td>
<td>( a )</td>
</tr>
<tr>
<td>proportional parameter for ( O_{\text{norm}A} )</td>
<td>( \varphi )</td>
</tr>
<tr>
<td>flexibility parameter for Y (regulation_change)</td>
<td>( \gamma_{1A} )</td>
</tr>
<tr>
<td>flexibility parameter for Y (maintenance_change)</td>
<td>( \gamma_{2A} )</td>
</tr>
<tr>
<td>flexibility parameter of agent A for the re-appraisal emotion regulation in (10)</td>
<td>( \lambda_A )</td>
</tr>
<tr>
<td>bias of agent A</td>
<td>( \beta_A )</td>
</tr>
<tr>
<td>flexibility parameter of Y (in a change expression); see (7), (8), (9), (10)</td>
<td>( \tau_{Y_A} )</td>
</tr>
</tbody>
</table>
10.4 Simulation Results
The model was implemented in different numerical software environments, one of which was Matlab. Multiple compositions of groups and networks were simulated, but for the sake of brevity, in this section the simulation scenario with only three agents are considered: namely; (A) a ‘depressed’ person with a very negative mood, (B) his/her life partner, and (C) his/her friend. Through this scenario, it is explored how the negative mood of a person can spread through his/her social network and can be controlled by emotion regulation mechanisms in the receiving persons. For all scenarios, the current simulations used the following parameters settings; $t_{\text{max}}=1000$, $\Delta t = 0.1$, flexibility parameters $\tau_{YA} = 0.5$ for openness, channel strength, expressiveness, and 0.1 for negative mood. These settings were obtained from previous systematic experiments to determine to the most suitable parameters values in the model. It means, several experiments were conducted to determine how a reasonable time scale and grain size of the simulation could be obtained. In this way, an appropriate setting for the parameters for speed of change, and of the time step $\Delta t$ was chosen. The other parameters in principle can be chosen in any form as they reflect characteristics of the situation modelled. Table 10.2 summarizes the (initial) settings for the different agents.

<table>
<thead>
<tr>
<th>Table 10.2. Individual Profiles for Each Agent</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Scenario #1</strong></td>
</tr>
<tr>
<td><strong>A</strong></td>
</tr>
<tr>
<td><strong>Initial M</strong></td>
</tr>
<tr>
<td>$M_{\text{norm}}$</td>
</tr>
<tr>
<td>$O_{\text{norm}}$</td>
</tr>
<tr>
<td>$E_{\text{norm}}$</td>
</tr>
<tr>
<td>$\lambda$</td>
</tr>
<tr>
<td>$B$</td>
</tr>
<tr>
<td>$\nu$ (for all openness $O$, channels $C$ and expressiveness $E$)</td>
</tr>
<tr>
<td>$\zeta$ (for all openness $O$, channels $C$ and expressiveness $E$)</td>
</tr>
</tbody>
</table>
Scenario # 1
The results of this scenario are shown in Fig. 10.2. During the simulation, the agent $A$ stays on his negative initial mood. He is not capable of regulating his mood (since he is too depressed; his emotion regulation mechanisms do not work) and transmits his negative mood to his partner and friend.

![Fig. 10.2. Simulation results scenario 1](image_url)

Because the partner and friend do have intact emotion regulation mechanisms, they are not infected to the level of the ‘depressed’ person’s negative mood. The stronger their emotion regulation mechanisms are, the less the ‘depressed’ person can infect them with his negative mood. Furthermore, agent $B$ has a higher negative mood bias ($\beta = 0.5$), than agent $A$ ($\beta = 0$), therefore, agent $B$’s negative mood decreases less fast than for agent $C$.

![Fig. 10.3. Simulation results scenario 2](image_url)
 Scenario #2
Here all agents have a maximum negative mood bias ($\beta = 1$), by which they all approximate the highest initial negative mood (in this case that of the ‘depressed’ person, agent $A$). If no agent would have working emotion regulation capacities, all agents would increase to a negative mood level of 0.9. Now agent $B$ and $C$ have small emotion regulation capacities and therefore, they do not fully increase to the initial mood level of agent $A$. Fig. 10.3 depicts the results for this scenario.

 Scenario #3
This scenario represents the baseline where no emotion regulation mechanisms exist in the three agents. In this case, all agents have a negative mood bias ($\beta = 0.5$), which has the effect that all the agent’s mood levels approximate the average initial mood setting (see Fig. 10.4).

![Fig. 10.4. Simulation results for scenario 3](image)

The emotion regulation mechanisms in agent $A$ and $B$, let the negative mood levels of agent $A$ and $B$ increase to a lesser extent. As can be seen from Fig. 10.4, this scenario shows how the negative bias $\beta$ and emotion regulation mechanism have opposite effects.

 Scenario #4
In this scenario, agent $C$ does not have working emotion regulation mechanisms, but agent $A$ and $B$ do. In Fig. 10.5 it is shown that the emotion regulation mechanisms in agent $A$ and $B$, let the negative mood levels of agent $A$ and $B$ decrease to a lesser extent, than that of Agent $C$, compared with scenario 3 (Fig. 10.5), where no agent had emotion regulation mechanisms that work. This shows how the negative bias $\beta$ and emotion regulation mechanism have opposite effects: A high negative bias ($\beta > 0.5$) can increase the negative
mood of the agent, intact emotion regulation mechanisms ($\lambda_A$ or $\nu$ of openness $O$, channel strength $C$ or expressiveness $E$ nonzero) will reduce this effect.

![Graph](image-url)

**Fig. 10.5. Simulation results for scenario 4**

### 10.5 Mathematical Analysis

In this section, an analysis is made of possible equilibria of the model. These are values for the variables of the model for which no change occurs. Taking as a point of departure the generic pattern,

$$Y_A(t+\Delta t) = Y_A(t) + \tau \cdot <\text{change expression}> \cdot \Delta t$$

and assuming $\tau$ nonzero, this is equivalent to $<\text{change expression}> = 0$ for all variables $Y_A$. Moreover, as

$$<\text{change expression}> = (1-Y_A(t)) \cdot \text{Pos}(<\text{basic change}>) - Y_A(t) \cdot \text{Pos}(-<\text{basic change}>)$$

the criterion for an equilibrium is:

$$(1-Y_A(t)) \cdot \text{Pos}(<\text{basic change}>) - Y_A(t) \cdot \text{Pos}(-<\text{basic change}>) = 0$$

Note that always $\text{Pos}(x) = 0$ or $\text{Pos}(-x) = 0$; this implies the following lemma:

**Lemma 1**

For any nonzero $\eta_1$ and $\eta_2$ it holds

$$\eta_1 \cdot \text{Pos}(x) + \eta_2 \cdot \text{Pos}(-x) = 0 \iff x = 0.$$  

By Lemma 1 it follows that for cases that $Y_A(t)$ is nonzero and $<1$, the equilibrium criterion is

$$<\text{basic change}> = 0$$
If this is applied to dynamic relations (7) to (10) the following four equilibrium equations are obtained:

\[
\begin{align*}
\zeta_{CA} \cdot [M_{normA} \cdot M_A] + \nu_{CA} \cdot [C_{normA} \cdot C_{BA}] &= 0 \\
\zeta_{OA} \cdot [M_{normA} \cdot M_A] + \nu_{OA} \cdot [O_{normA} \cdot O_A] &= 0 \\
\zeta_{EA} \cdot [M_{normA} \cdot M_A] + \nu_{EA} \cdot [E_{normA} \cdot E_A] &= 0 \\
\beta_A \cdot (1 - (1 - M_A) \cdot (1 - M_A^*)) + (1 - \beta_A) \cdot M_A \cdot M_A^* + \lambda_A \cdot [M_{normA} \cdot M_A] &= 0
\end{align*}
\]

(11) - (14)

The first three equations are equivalent to (here the following short notation is used: \(devY = Y_{norm} - Y\) (deviation of \(Y\) from norm value):

\[

devc_{BA} = - \left( \frac{\zeta_{CA}}{\nu_{CA}} \right) \cdot devM_A \\
devo_A = - \left( \frac{\zeta_{OA}}{\nu_{OA}} \right) \cdot devM_A \\
deve_A = - \left( \frac{\zeta_{EA}}{\nu_{EA}} \right) \cdot devM_A
\]

from (11) - (13)

In particular, it follows that either none of \(C_{BA}, O_{A}, E_{A}, M_A\) deviates from its norm, or all of them deviate from their norm (in a proportional manner). For the special case \(M_{normA} = 0\) used in the experiments, it holds \(devM_A = -M_A\), and therefore the equations are:

\[

devc_{BA} = \left( \frac{\zeta_{CA}}{\nu_{CA}} \right) \cdot M_A \\
devo_A = \left( \frac{\zeta_{OA}}{\nu_{OA}} \right) \cdot M_A \\
deve_A = \left( \frac{\zeta_{EA}}{\nu_{EA}} \right) \cdot M_A
\]

Having exploited the first three equations, what remains is the fourth one. To analyse this one, the following lemma is useful.

**Lemma 2**

For any \(A\) it holds:

\(M_A^* = 0\) iff \(M_B = 0\) for all \(B \neq A\) with nonzero \(CS_{BA}\)

\(M_A^* = 1\) iff \(M_B = 1\) for all \(B \neq A\) with nonzero \(CS_{BA}\)

As the fourth equation is rather complex in its general form, it is analysed for a number of special cases. In particular, assume \(\lambda_A = 0\) (no re-appraisal). Then the fourth equation can be rewritten as follows:

\[
\beta_A \cdot M_A^* - M_A \cdot [(1 - \beta_A) \cdot M_A^* + 2\beta_A \cdot M_A^*] = 0
\]

\[
M_A = \frac{\beta_A \cdot M_A^*}{[(1 - \beta_A) \cdot (1 - M_A^*) + \beta_A \cdot M_A^*]}, \quad \text{if} \quad (1 - \beta_A) \cdot (1 - M_A^*) + \beta_A \cdot M_A^* \neq 0
\]
For this case, equilibria can occur with values different from 0 and 1, which may depend on the initial values. In addition, three special cases for $\beta_A$ are considered: $\beta_A = 0, \beta_A = 0.5, \beta_A = 1$.

**Case I. $\lambda_A = 0, \beta_A = 0$**

In this case the fourth equation can be rewritten into

$$M_A - M_A^* - M_A = 0,$$

which is equivalent to

$$M_A = 0 \text{ or } M_A^* = 1$$

By Lemma 2 this is equivalent to

$$M_A = 0 \text{ or } M_B = 1 \text{ for all } B \neq A \text{ with nonzero } CS_{B,A}$$

This implies that for this case no equilibria exist with values different from 0 and 1.

**Case II. $\lambda_A = 0, \beta_A = 0.5$**

In this case the fourth equation can be rewritten into

$$0.5(M_A + M_A^* - M_A M_A^*) + 0.5 M_A M_A^* - M_A = 0,$$

which is equivalent to $M_A = M_A^*$

For this case equilibria can occur with values different from 0 and 1, which may depend on the initial values.

**Case III. $\lambda_A = 0, \beta_A = 1$**

In this case the fourth equation can be rewritten into

$$M_A - M_A M_A^* = 0$$

which is equivalent to

$$M_A = 1 \text{ or } M_A^* = 0$$

By Lemma 2 this is equivalent to

$$M_A = 1 \text{ or } M_B = 0 \text{ for all } B \neq A \text{ with nonzero } CS_{B,A}$$
As for Case I, this implies that for this case no equilibria exist with values different from 0 and 1.

10.6 Discussion
Research into the mechanisms of emotion regulation and social contagion has mainly been conducted separately [2, 13, 15]. In the current work, it was investigated how these processes work in an integrated manner, by means of a computational model. An agent-based model is proposed, that formalizes and simulates the integrated contagion and regulation of negative mood. The current model was inspired by a number of theories, namely emotion contagion and Gross’ emotion regulation theory [1, 2, 5, 7]. For short time durations, contagion may be the main factor determining the mood of a person; however, for longer time durations individuals also apply regulation mechanisms to compensate for too strong deviations of their mood.

Computational contagion models usually do not take into account such regulation.

Simulation results show interesting patterns that illustrate the combined effect of negative mood contagion and emotion regulation. Together, these elements can be used to understand how a person is capable to maintain his or her mood, while maintaining social interactions with another person. For this model, a mathematical analysis shows how such equilibria are indeed possible for the model. Note that for the sake of simplicity mood affecting external events during a simulated process have been left out of consideration. However, it is not difficult to include them too.

In follow up research, more attention will be focused to implement this model in a large scale social networks and to see important emergent behaviours that possibly exist when more agents are involved. Furthermore, it would be interesting to study a situation at a societal level where agents can also change their behaviours (such as relapse, recovery, and susceptibility), by introducing additional attributes and parameters into the model. In addition, this model can be used as a foundation to design software agents that capable to understand and aware about humans and their interactions. By using this model, software agents will use this as knowledge to provide appropriate actions to support humans pertinent to their predicted states (e.g. the level of negative mood). Future work of this model can be extended to incorporate multiple types of emotion and their interaction. Moreover, this model has a potential to be useful to provide a foundation to understand how negative mood can be propagated via social media (e.g., Facebook, MySpace, Twitter).
References


Part V: Modelling Team and Leadership Dynamics

Abstract. In Part V, agent-based models that can simulate team and leadership dynamics are proposed. In Chapter 11, an intelligent support agent that can support group development is designed and evaluated. The proposed model is based on situational leadership theory and monitors and analyses group development overtime. It can propose effective leadership behaviour to the team leader, in order to let the group perform as effectively as it can. The model was evaluated by automatic property checking. In Chapter 12, the communication during crisis management of a real-life incident “fire in the Amsterdam Airport Schiphol train tunnel” was formalised into an empirical trace. Due to miscommunication, three trains had to hold for more than thirty minutes in the train tunnel during a fire. This led to very anxious passengers and was a near miss situation: many people could have died if the fire would not have gone out by itself. It is shown how automatic property checking can be an efficient way to analyse (mistakes in) communication during incident management. Also, it is a first step towards designing an agent-based model that can simulate multiple incident management scenario’s to find out which management style is most effective.
Chapter 11 - Computational Model-Based Design of Leadership Support Based on Situational Leadership Theory

Tibor Bosse, Rob Duell, Zulfiqar A. Memon, Jan Treur, C. Natalie van der Wal

Abstract This chapter introduces a design of an agent-based leadership support system exploiting a computational model for development of individuals or groups. It is to be used, for example, as a basis for systems to support a group leader in the development of individual group members or a group as a whole. Using a computational model for Situational Leadership Theory and model-based reasoning techniques, the system monitors and analyses the development level over time and provides support to the group leader by proposing for different points in time the most effective leadership behaviour according to Situational Leadership Theory. The support model has been formally designed and within a dedicated software environment, simulation experiments have been performed.

Part of this chapter appeared as:

11.1 Introduction
One of the important factors that affect team performance is development within a group. Multiple (informal) models of development of individuals or a group have been suggested by different researchers. For example, the models of Tubbs, Fisher and Tuckman, see [5], [12], and [16]. These three models all tend to suggest a similar development. In well-known models of Tubbs, Fisher and Tuckman, 4 or 5 stages are suggested, through which the group develops. For example, the first two stages in Tubbs and Fisher’s theory are called ‘orientation’ and ‘conflict’. In the ‘orientation’ stage, the group experiences the first awkward feelings and tensions that have to do with the fact that the group members get to know each other and have to establish communication rules and expectations. In the ‘conflict’ stage the group debates about the different ideas they form on how they can perform the task they are appointed. The first two stages in Tuckman’s theory are called forming and storming and can also be summarized by: (1) getting to know each other in the group, and after (2) starting to discuss the group ideas and group status. The subsequent stages, which are called different in each theory describe how the group starts to perform the task, selects ideas and actions from all the alternatives that emerged in the previous stages, reaches final decisions and completes the task.

Leadership can be defined as the process of influencing activities of an individual or a group towards goal achievement in a given situation [6, p. 86]. Different leadership models focus on different aspects that can define how effective a leader can be in guiding the team or individual towards a goal. Some models focus on the traits of the leader and followers [8], others on their attitudes and even other models on the situational context or organisational dynamics. Examples of the attitudinal approaches to leadership are the studies in [7], [9]. There are also models that focus on the on the situational context or organisational dynamics. The situational approaches to leadership focus on the behaviours that the leader and followers show in different situational contexts. It is posed that leaders can increase their effectiveness by education, training and development. A leader is not constrained by certain inborn abilities or traits. A leader can acquire and increase his or her skills. An example of a situational approach to situational leadership is the Tannenbaum-Schmidt continuum of leader behaviour [15]. In this model the leader can choose one of 7 possible behaviours, depending on the leader, follower and situational variables. The different behaviours a leader can choose from come from 2 dimensions: democratic/relationship oriented versus authoritarian/task oriented behaviour. Another well-known situational model of leadership is Fiedler’s
contingency model. [4]. Fiedler suggests which situational variables are most favourable to a leader in a given situation.

The current chapter introduces a support model which is based on a computational model of the situational leadership theory of Hersey and Blanchard [6, pp.171-204] (see also [14], [11], [10]). Their model differs from most other leadership models in that they added a third dimension of leadership behaviour: the effectiveness dimension. The other two dimensions of leadership behaviour are the task-oriented and relationship oriented behaviours taken from [7], [9]. With the integration of the third dimension, it is now possible to predict the effectiveness of the different leadership styles in the specific situational context or situational demands. In this model also four development stages are suggested. In this theory, a group member can be called a follower, as in the follower of the leader. This model was chosen because it focuses more on the behaviour of the follower.

As the authors of [6] write:

‘In Situational Leadership, it is the follower who determines the appropriate leader behavior. The follower can get any behavior desired depending upon the follower’s behavior.’ [6, p.188].

This is interesting for a multi-agent model, since the follower-agent would then show behaviour on which the leader-agent responds. In other words the behavioural concepts of the follower and leader agents would be: the leader being responsive and follower pro-active. The leader only responds to the behaviour of the follower, which he categorizes in a certain development level. The follower however can adapt. With appropriate leadership behaviour he or she can grow to a higher development level. The follower’s behaviour determines the leader’s behaviour.

The motivation for formalising a computational leadership model originated from the goal to design a software agent that supports effective team performance. At present no computational models of (situational) leadership are available. This chapter explores the possibility of a support model for group or individual development based on a situational leadership model. The idea is that a supporting agent can estimate the development level of a group or group member and match this with an appropriate leadership style. Then, based on the leadership style and the context, which also reflects the history and communication with the group or group member, it can propose effective leadership behaviours to the team leader.

In the description of the detailed model in the next sections, the temporal relation \(a \rightarrow b\) denotes that when a state property \(a\) occurs, then after a certain time delay (which for each relation instance can be specified as any positive real number), state property \(b\) will occur. In this language (called LEADSTO) both
temporal logical relationships and numerical calculations can be specified, and a dedicated software environment is available to support specification and simulation; for more details see [3].

Below, in Section 11.2, a detailed model of the dynamics of a development level is explained and formalised. Section 11.3 introduces the main aspects of a support model for development, which can be used by a software agent to provide support by proposing the group leader the most effective leadership behaviour. In Section 11.4, simulation results of the development level and the support mechanisms are shown. Finally, Section 11.5 concludes the chapter with a discussion.

11.2 A Model for Dynamics of Development Levels

A model for development should address different development stages or levels a group or group member follows and indicate how transfer from one stage/level to the next level takes place. Multiple (informal) models of development have been suggested by different researchers; for example, see [5] and [16]. For the current chapter the Situational Leadership Theory [6] was adopted; see also, for example, [14], [11], [10]. In this theory, the group leader is responsive to the behaviour of the group or group member, which the leader categorises in one of four development levels. In this way the group or group member’s behaviour determines the group leader’s behaviour. By showing appropriate leadership behaviour, a higher development level can be reached.

<table>
<thead>
<tr>
<th>Ability:</th>
<th>Willingness:</th>
</tr>
</thead>
<tbody>
<tr>
<td>Knowledge</td>
<td>Confidence</td>
</tr>
<tr>
<td>Skill</td>
<td>Commitment</td>
</tr>
<tr>
<td>Experience</td>
<td>Motivation</td>
</tr>
<tr>
<td>Understanding a task</td>
<td>Assurance in task performance</td>
</tr>
<tr>
<td>Task proficiency</td>
<td>Demonstrating duty to perform a task</td>
</tr>
<tr>
<td>The ability gained from task performance</td>
<td>The desire to perform a task</td>
</tr>
</tbody>
</table>

In [6] the authors define development levels as what they call ‘readiness’ levels of a group or individual person. They define readiness as the extent to which a follower or group shows the ability and willingness to accomplish a specific task. Readiness is not a personality characteristic, but is a concept that is being used in a specific situation, for a specific task. Their theory states that readiness exists of two components: ability and willingness. They define ability as the experience, skill or knowledge of the person or group and willingness as the degree of confidence, commitment and motivation a person or group has...
in accomplishing a specific task. More specific definitions of the ability and willingness sub-components, taken from p.176-177 in [8], are listed in Table 11.1.

The interaction between the two components ability and willingness defines the current development level of a person or group. A person or group can be able or unable and willing or unwilling in task performance. Of these four states, four combinations can be made, which define the four development levels or readiness levels of a person or group. Thus the continuum of possibilities of the readiness of a person or group can be structed according to four levels: R1, R2, R3 and R4, see Figure 11.1 (comparable to Figure 8-2, p.177 in [6]). Here R1 defines a development level where the person or group is unable and unwilling. The unwillingness is either the lack of commitment and motivation or the lack of confidence in task performance. In R2 the group or person is unable but willing. Willingness can be either motivation and commitment the group or person demonstrates, or the confidence the person or group demonstrates in the guided task performance. In development level R3, the person or group is able but unwilling. This means that the group or person now has the ability (experience, skill and knowledge) to perform a task, but that the group or person lacks commitment and motivation or lacks confidence. In R4 the group or person is able and willing. This means that the group or person is able to perform a task and has the motivation and commitment or shows confidence in performing the task.

![Figure 11.1. Continuum of readiness](image)

The readiness continuum can be expanded by behavioural indicators for every level. These behavioural indicators have been defined in [8]. A short summary of the behavioural indicators is given below in Table 11.2. Note that readiness levels R1 and R3 are divided into two sub-levels, because the theory states that it is important to assess whether a person is either unable and unwilling or unable and insecure.

The current development level of a group (member) is reflected in the aspect $g_R$ with possible values R1, R2, R3 and R4 for R. These four values reflect the four different stages shown in Figure 11.1, taken from the situational leadership theory in [6]. Each profile attribute $p_{ij}$ can be seen as a category or behavioural category of a certain development level. Index $i$
defines the development level: \( i \in \{1, 2, 3, 4\} \). Index \( j \) defines the attribute name/position within this development level, for example for \( i = 1: j \in \{1, 2, 3, 4, 5, 6, 7, 8, 9, 10\} \). For example profile attribute \( p_{11} \) ‘defensiveBehaviour’ belongs to development level R1 and is the first attribute name of this development level. This profile attribute reflects the degree to which the group (member) shows defensive behaviour. Therefore it has a negative meaning. In the proposed model of group development, 10 profile attributes are suggested for development level R1, 9 for development level R2 and 7 both for levels R3 and R4, see Table 11.3.

**Table 11.2. Behavioural indicators of the four readiness levels**

<table>
<thead>
<tr>
<th>Level</th>
<th>Indicators</th>
</tr>
</thead>
<tbody>
<tr>
<td>R1: unable and unwilling</td>
<td>Defensive, complaining, argumentative behaviours</td>
</tr>
<tr>
<td></td>
<td>Latent task completion</td>
</tr>
<tr>
<td></td>
<td>Intense frustration</td>
</tr>
<tr>
<td></td>
<td>Performance only to exact request</td>
</tr>
<tr>
<td>R1: unable and insecure</td>
<td>Discomfort in body language</td>
</tr>
<tr>
<td></td>
<td>Confused, unclear behaviour</td>
</tr>
<tr>
<td></td>
<td>Concern over possible outcomes</td>
</tr>
<tr>
<td></td>
<td>Fear of failure</td>
</tr>
<tr>
<td>R2: unable but willing</td>
<td>Speaking intense and quickly</td>
</tr>
<tr>
<td>or unable but confident</td>
<td>Making 'yes I know' comments</td>
</tr>
<tr>
<td></td>
<td>Listening carefully</td>
</tr>
<tr>
<td></td>
<td>Accepting tasks</td>
</tr>
<tr>
<td></td>
<td>Acting quickly</td>
</tr>
<tr>
<td>R3: able but unwilling</td>
<td>Being hesitant or resistant</td>
</tr>
<tr>
<td></td>
<td>Feeling overworked and over-obligated</td>
</tr>
<tr>
<td></td>
<td>Seeking reinforcement</td>
</tr>
<tr>
<td>R3: able but insecure</td>
<td>Questioning one's own ability</td>
</tr>
<tr>
<td></td>
<td>Focusing on potential problems</td>
</tr>
<tr>
<td></td>
<td>Lacking self-esteem</td>
</tr>
<tr>
<td>R4: able and willing</td>
<td>Keeping boss informed of task progress</td>
</tr>
<tr>
<td>or able and confident</td>
<td>Being responsible and result-oriented</td>
</tr>
<tr>
<td></td>
<td>Being willing to help others</td>
</tr>
<tr>
<td></td>
<td>Sharing creative ideas</td>
</tr>
<tr>
<td></td>
<td>Making efficient use of resources</td>
</tr>
</tbody>
</table>
Table 11.3. Formal representations of the behavioural indicators of the four readiness levels, Profile Attribute Names/Values and Experience Names/Values

<table>
<thead>
<tr>
<th>Development level</th>
<th>Profile attribute name of $p_j$</th>
<th>Meaning</th>
<th>Profile attribute value $v_{ij}$</th>
<th>Experience name $n_{ij}$</th>
<th>Experience value $e_{ij}$</th>
</tr>
</thead>
<tbody>
<tr>
<td>R1</td>
<td>Defensive behaviour</td>
<td>negative</td>
<td>$v_{11}$</td>
<td>$n_{11}$</td>
<td>$e_{11}$</td>
</tr>
<tr>
<td></td>
<td>Complaining behaviour</td>
<td>negative</td>
<td>$v_{12}$</td>
<td>$n_{12}$</td>
<td>$e_{12}$</td>
</tr>
<tr>
<td></td>
<td>Intense frustration</td>
<td>negative</td>
<td>$v_{13}$</td>
<td>$n_{13}$</td>
<td>$e_{13}$</td>
</tr>
<tr>
<td></td>
<td>Late_task_completion</td>
<td>negative</td>
<td>$v_{14}$</td>
<td>$n_{14}$</td>
<td>$e_{14}$</td>
</tr>
<tr>
<td></td>
<td>Performance_only_to_exact_request</td>
<td>negative</td>
<td>$v_{15}$</td>
<td>$n_{15}$</td>
<td>$e_{15}$</td>
</tr>
<tr>
<td></td>
<td>Argumentative Behaviour</td>
<td>negative</td>
<td>$v_{16}$</td>
<td>$n_{16}$</td>
<td>$e_{16}$</td>
</tr>
<tr>
<td></td>
<td>Discomfort_in_body_language</td>
<td>negative</td>
<td>$v_{17}$</td>
<td>$n_{17}$</td>
<td>$e_{17}$</td>
</tr>
<tr>
<td></td>
<td>Confused_unclearBehaviour:</td>
<td>negative</td>
<td>$v_{18}$</td>
<td>$n_{18}$</td>
<td>$e_{18}$</td>
</tr>
<tr>
<td></td>
<td>Fear_of_failure</td>
<td>negative</td>
<td>$v_{19}$</td>
<td>$n_{19}$</td>
<td>$e_{19}$</td>
</tr>
<tr>
<td></td>
<td>Concern_over_possible_outcomes</td>
<td>negative</td>
<td>$v_{110}$</td>
<td>$n_{110}$</td>
<td>$e_{110}$</td>
</tr>
<tr>
<td>R2</td>
<td>Nodding_head</td>
<td>positive</td>
<td>$v_{21}$</td>
<td>$n_{21}$</td>
<td>$e_{21}$</td>
</tr>
<tr>
<td></td>
<td>Seeming_eager</td>
<td>positive</td>
<td>$v_{22}$</td>
<td>$n_{22}$</td>
<td>$e_{22}$</td>
</tr>
<tr>
<td></td>
<td>Speaking_intense_and_quickly</td>
<td>positive</td>
<td>$v_{23}$</td>
<td>$n_{23}$</td>
<td>$e_{23}$</td>
</tr>
<tr>
<td></td>
<td>Listening_carefully</td>
<td>positive</td>
<td>$v_{24}$</td>
<td>$n_{24}$</td>
<td>$e_{24}$</td>
</tr>
<tr>
<td></td>
<td>Accepting_tasks</td>
<td>positive</td>
<td>$v_{25}$</td>
<td>$n_{25}$</td>
<td>$e_{25}$</td>
</tr>
<tr>
<td></td>
<td>Acting_quickly</td>
<td>positive</td>
<td>$v_{26}$</td>
<td>$n_{26}$</td>
<td>$e_{26}$</td>
</tr>
<tr>
<td></td>
<td>Seeking_clarity</td>
<td>positive</td>
<td>$v_{27}$</td>
<td>$n_{27}$</td>
<td>$e_{27}$</td>
</tr>
<tr>
<td></td>
<td>Making_yes_I_know_comments</td>
<td>positive</td>
<td>$v_{28}$</td>
<td>$n_{28}$</td>
<td>$e_{28}$</td>
</tr>
<tr>
<td></td>
<td>Answering_questions_superficially</td>
<td>negative</td>
<td>$v_{29}$</td>
<td>$n_{29}$</td>
<td>$e_{29}$</td>
</tr>
<tr>
<td>R3</td>
<td>Being_hesitant</td>
<td>negative</td>
<td>$v_{31}$</td>
<td>$n_{31}$</td>
<td>$e_{31}$</td>
</tr>
<tr>
<td></td>
<td>Being_resistant</td>
<td>negative</td>
<td>$v_{32}$</td>
<td>$n_{32}$</td>
<td>$e_{32}$</td>
</tr>
<tr>
<td></td>
<td>Feeling_overworked</td>
<td>negative</td>
<td>$v_{33}$</td>
<td>$n_{33}$</td>
<td>$e_{33}$</td>
</tr>
<tr>
<td></td>
<td>Seeking_reinforcement</td>
<td>negative</td>
<td>$v_{34}$</td>
<td>$n_{34}$</td>
<td>$e_{34}$</td>
</tr>
<tr>
<td></td>
<td>Feeling_over-obligated</td>
<td>negative</td>
<td>$v_{35}$</td>
<td>$n_{35}$</td>
<td>$e_{35}$</td>
</tr>
<tr>
<td></td>
<td>Lacking_self-esteem</td>
<td>negative</td>
<td>$v_{36}$</td>
<td>$n_{36}$</td>
<td>$e_{36}$</td>
</tr>
<tr>
<td></td>
<td>Focusing_on_potential_problems</td>
<td>positive</td>
<td>$v_{37}$</td>
<td>$n_{37}$</td>
<td>$e_{37}$</td>
</tr>
<tr>
<td>R4</td>
<td>Sharing_creative_ideas</td>
<td>positive</td>
<td>$v_{41}$</td>
<td>$n_{41}$</td>
<td>$e_{41}$</td>
</tr>
<tr>
<td></td>
<td>Being_result-oriented</td>
<td>positive</td>
<td>$v_{42}$</td>
<td>$n_{42}$</td>
<td>$e_{42}$</td>
</tr>
<tr>
<td></td>
<td>Being_willing_to_help_others</td>
<td>positive</td>
<td>$v_{43}$</td>
<td>$n_{43}$</td>
<td>$e_{43}$</td>
</tr>
<tr>
<td></td>
<td>Keeping_boss_informed_of_task</td>
<td>positive</td>
<td>$v_{44}$</td>
<td>$n_{44}$</td>
<td>$e_{44}$</td>
</tr>
<tr>
<td></td>
<td>Shows_confidence</td>
<td>positive</td>
<td>$v_{45}$</td>
<td>$n_{45}$</td>
<td>$e_{45}$</td>
</tr>
<tr>
<td></td>
<td>Making_efficient_use_of_resources</td>
<td>positive</td>
<td>$v_{46}$</td>
<td>$n_{46}$</td>
<td>$e_{46}$</td>
</tr>
<tr>
<td></td>
<td>Being_responsible</td>
<td>positive</td>
<td>$v_{47}$</td>
<td>$n_{47}$</td>
<td>$e_{47}$</td>
</tr>
</tbody>
</table>
Table 11.3 also shows that each profile attribute \( p_{ij} \) has a profile attribute value \( v_{ij} \) which reflects how often the group (member) has shown certain behaviours that indicate the specific profile attribute. Aspect \( v_{ij} \) has been formalised numerically by numbers in the interval \([0, 1]\). For example \( v_{47} = 0.5 \) means that the group (member) has shown certain behaviours that indicate that the group member is being responsible. The exact dynamics of these profile attribute values depend on the settings of the other parameters, as explained below. Each profile attribute \( p_{ij} \) has a default profile attribute value \( v_{ij} \). The default value of \( v_{ij} \) depends on the positive or negative meaning of the profile attribute \( p_{ij} \). A profile attribute \( p_{ij} \) with a positive meaning has a default value 0.1 for \( v_{ij} \) and one with a negative meaning has a default value of 0.9 for \( v_{ij} \). For example the profile attribute \( p_{18} \) which is ‘confused_unclear Behaviour’ has a negative meaning. For this reason it is chosen that the default profile value of \( v_{18} \) is 0.9. Whenever the group (member) will show behaviour that corresponds with this profile attribute \( p_{18} \), the profile attribute value \( v_{18} \) will decrease. A profile attribute \( p_{ij} \) with a positive meaning, for example \( p_{25} \) ‘accepting_tasks’, will have a default value of 0.1 for \( v_{25} \). If the group (member) shows behaviour that corresponds with this profile attribute \( p_{25} \), this profile attribute value \( v_{25} \) will increase. The idea is that the group (member) will follow the group development level from R1, to R2, to R3 to R4, by slowly increasing or decreasing certain profile attribute values \( p_{ij} \). How this mechanism works is explained using the other aspects shown in Table 11.3.

In Table 11.3 also the concept experience name \( n_{ij} \) with experience value \( e_{ij} \) is introduced, which reflects the degree to which certain behaviour indicates a certain profile attribute \( p_{ij} \). Aspect \( e_{ij} \) has been formalised numerically by numbers in the interval \([0, 1]\). If a profile attribute value \( p_{ij} \) has a positive meaning, then the higher the value of \( e_{ij} \) the more this behaviour is an indication of the corresponding profile attribute \( p_{ij} \). This is opposed to \( e_{ij} \)’s that indicate profile attribute behaviours with a negative meaning. Therefore a value of 0.2 for \( e_{11} \) reflects the same degree of \( p_{11} \) as the value of 0.8 for \( e_{21} \) that reflects \( p_{21} \). More specifically, in both cases the behaviour indicates the profile attribute to an extent of 80%. For example, behaviour ‘crossed_arms’ has an experience value \( e_{11} \) of 0.2 (negative meaning), and behaviour ‘nods_head’ has an experience value \( e_{21} \) of 0.8 (positive meaning). In this example ‘crossed_arms’ indicates profile attribute \( p_{11} \) ‘defensive behaviour’ just as strong as ‘nods_head’ indicates profile attribute \( p_{21} \) ‘nodding_head’, namely they both indicate their \( p_{ij} \) with 80%.

The next step is to maintain each profile attribute value \( v_{ij} \). The formula for updating the profile attribute values \( v_{ij} \) is expressed as follows:
If \( v_{ij} \) has a positive meaning

\[ \text{new } v_{ij} = a v_{ij} + (1-a)e_{ij} \]

If \( v_{ij} \) has a negative meaning

\[ \text{new } v_{ij} = 1-\left[a(1-v_{ij}) + (1-a)(1-e_{ij})\right] \]

Here \( a \) is a number in the interval \([0, 1]\) which reflects how persistent the \( p_{ij} \) value is. If \( a = 0 \) then every new experience ‘overwrites’ the old profile attribute value \( v_{ij} \) completely. If \( a \) is a high number, like 0.8, then the ‘old’ profile attribute value \( v_{ij} \) is very persisting, since the new experience can adjust only 20% of the ‘old’ profile attribute \( v_{ij} \) into the ‘new’ profile attribute \( v_{ij} \). Note that for the second formula:

\[
1- \text{new } v_{ij} = a(1-v_{ij}) + (1-a)(1-e_{ij}),
\]

is equivalent with:

\[
\text{new } v_{ij} = 1-\left[a(1-v_{ij}) + (1-a)(1-e_{ij})\right].
\]

As an example: if the value of \( v_{11} \) (negative meaning) is 0.9 at time point 1, the group shows a defensive behaviour with \( e_{11} = 0.2 \), and \( a \) is set to 0.5. Then the new value for \( v_{11} \) at time point 2 will be: \( 1-\left[0.5(1-0.9) +0.5(1-0.2)\right] = 0.55 \).

Expressed in differential equation format, the update mechanism for profile attribute \( p_{ij} \) is as follows:

\[
\begin{align*}
\frac{d p_{ij}(t)}{dt} & = \beta \left( e_{ij}(t) - p_{ij}(t) \right) \\
\text{d } p_{ij}(t)/\text{dt} & = \beta \left( e_{ij}(t) - p_{ij}(t) \right)
\end{align*}
\]

where \( \beta = 1 - a \) can be considered a flexibility factor.

The final step is to calculate \( q_i \) for each development level, which indicates the degree the group (member) has shown behaviours of the specific development level. Aspect \( q_i \) has been formalised numerically by numbers in the interval \([0, 1]\) and reflects the average of the profile attribute values \( p_{ij} \) of the corresponding development level. For example, \( q_i \) is the average of all \( p_{ij} \) with index \( i = 1 \). If \( q_i \) is 0.1, then the group (member) has not shown any behaviours yet that are indicative of development level R1, since it is the average of all (rescaled) default profile values \( v_{ij} \). The formula for averaging the profile attributes \( p_{ij} \) into \( q_i \) is:

\[
q_i = \frac{\sum_{j=1}^{n} w_{ij}}{n_j}
\]

where, \( n_1 = 10, n_2 = 9, n_3 = 7, \) and \( n_4 = 7 \), and \( w_{ij} = v_{ij} \) if the meaning is positive and \( w_{ij} = 1-v_{ij} \) if the meaning is negative.
The group (member) will reach a next development level by exceeding a certain threshold for each \( q_i \). Below a threshold of 0.6 was chosen, but the threshold can be set to any other number that will provide predictive behaviour of the group. The mechanism of transferring to a next development level by exceeding a threshold is expressed by the following four rules:

- If \( q_1 < 0.6 \ & \ q_2 < 0.6 \ & \ q_3 < 0.6 \) then development level is \( g_{R1} \)
- If \( q_1 \geq 0.6 \ & \ q_2 < 0.6 \ & \ q_3 < 0.6 \) then development level is \( g_{R2} \)
- If \( q_1 \geq 0.6 \ & \ q_2 \geq 0.6 \ & \ q_3 <0.6 \) then development level is \( g_{R3} \)
- If \( q_1 \geq 0.6 \ & \ q_2 \geq 0.6 \ & \ q_3 \geq 0.6 \) then development level is \( g_{R4} \)

11.3 The Leadership Support Model

In the previous section, the development level model has been discussed. In this section, a support model is introduced that uses this model to provide intelligent support to the group leader by proposing the most effective leadership behaviour to the group leader. The idea here is that a software agent can estimate the development level of the group (member) and match this with the appropriate leadership style. Then based on the leadership style and the context, which reflects the history and communication with the group (member), it can propose the most effective leadership behaviours to the team leader. In Figure 11.2 below, an overview of these processes of the support model is depicted. Although the proposed model is not a classification model, it has an overall structure similar to what is sometimes used in classification models [13], namely: abstraction, matching and refinement. The left part of Figure 11.2 (abstraction) represents model-based reasoning using the development level model described in the previous section to analyse the group member behaviour, and the right part (refinement) represents how to obtain support based on the analysis.

![Figure 11.2. Abstract view of Leadership Support Model](image-url)
The matching process in Figure 11.2 is based on [6], where four leadership styles are proposed that match with one of the four development levels discussed in previous section. The four leadership styles \( \{S1, S2, S3, S4\} \) are four different combinations of behaviours that are low or high on two dimensions: task behaviour and relationship behaviour.

Typical task behaviour is telling people what to do, how to do it, where to do it and who should do it. The leader spells out the responsibilities and duties of the group (member). Relationship behaviour is characterised by two-way communication: the encouragement, listening, facilitating, and supportive behaviours. Table 11.4 and Figure 11.3 give an overview of the four leadership styles. Figure 11.3 is inspired by figure 8-1 in [5, p.174].

<table>
<thead>
<tr>
<th>Leadership Style</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>( S1 )</td>
<td>High task-behaviour and low relationship behaviour</td>
</tr>
<tr>
<td>( S2 )</td>
<td>High task and high relationship behaviour</td>
</tr>
<tr>
<td>( S3 )</td>
<td>High relationship and low task behaviour</td>
</tr>
<tr>
<td>( S4 )</td>
<td>Low relationship and low task behaviour</td>
</tr>
</tbody>
</table>

![Figure 11.3. Leadership Styles in four Quadrants](image)

The correct matches of each leadership style with one of the readiness levels of the group member(s) are defined in [6] as: R1 matches \( S1 \), R2 matches \( S2 \), R3 matches \( S3 \) and R4 matches \( S4 \). In [6] this is depicted as a Gaussian curve that goes through the four leadership style quadrants (see Figure 11.4, upper part). Beneath the four quadrants, the four development stages are depicted. The developmental stage that matches with an interval on the horizontal axis of the quadrants, matches with part of the Gaussian curve in that interval. The quadrant that is traversed by the Gaussian curve in that interval is the matching leadership style for that development level.
Figure 11.4 (upper part), (inspired from Figure 8-7 in [6, p.182]) gives an overview of the four leadership styles.

![Situational Leadership Model: Leadership styles in four quadrants (upper part), related to the four readiness levels (lower part)](image)

**Figure 11.4.** Situational Leadership Model: Leadership styles in four quadrants (upper part), related to the four readiness levels (lower part)

In order for the software system to support the group leader in the development of group member(s) in an appropriate manner, LEADSTO [3] rules are specified. In Table 11.5 below, examples of the logical formalization incorporating the numerical and textual representations are shown. Table 11.6 shows the ontology needed to express such rules. The contents of Table 11.5 and Table 11.6, belong to an example scenario (also used to simulate in the next section) that represents a situation in which a PhD student is developing himself in conducting explorative research and is guided in his development by a professor.

**Table 11.5.** Examples of Logical Formalization of Different Concepts

<table>
<thead>
<tr>
<th>Concept</th>
<th>Formalization</th>
</tr>
</thead>
<tbody>
<tr>
<td>Person $A$ communicates COM to person $B$ in context $C$</td>
<td>communication_by_to_in(COM:COMMUNICATION, $A$: AGENTS, $B$: AGENTS, $C$: CONTEXT)</td>
</tr>
<tr>
<td>Person $S$ shows body language $B$ in context $C$</td>
<td>body_language_of_in($B$:BODY_LANGUAGE, $S$:AGENT, $C$:CONTEXT)</td>
</tr>
</tbody>
</table>
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<table>
<thead>
<tr>
<th>Sort</th>
<th>Description of use</th>
<th>(example) elements</th>
</tr>
</thead>
<tbody>
<tr>
<td>AGENTS</td>
<td>The group members (a student, professor and the external world)</td>
<td>Professor_agent, student_agent, external_world</td>
</tr>
<tr>
<td>SUB_COMPONENTS_PROFESSOR</td>
<td>The reasoning components inside the professor</td>
<td>aim, wim, analysis, action_determination,</td>
</tr>
<tr>
<td>SUB_COMPONENTS_ANALYSIS_PROFESSOR</td>
<td>The subcomponents of the reasoning component analysis inside the professor</td>
<td>behaviour_profiling, development_level_determination</td>
</tr>
<tr>
<td>SUB_COMPONENTS_ACTION_DETERMINATION_PROFESSOR</td>
<td>The subcomponents of the reasoning component action determination inside the professor</td>
<td>leadership_style_determination, action_selection</td>
</tr>
<tr>
<td>BODY_LANGUAGE</td>
<td>Body language of group members</td>
<td>Nods_head, lifted_eyebrow, crossed_arms</td>
</tr>
<tr>
<td>STUDENT_BODY_LANGUAGE</td>
<td>Student’s body language</td>
<td>Smiling</td>
</tr>
<tr>
<td>PROFESSOR_BODY_LANGUAGE</td>
<td>Professor’s body language</td>
<td>Smiling</td>
</tr>
<tr>
<td>COMMUNICATION</td>
<td>Communication of group members</td>
<td>How_do_I_do_that, do_i_really_have_to_do_this_task, I_really_like_to_do_this_task</td>
</tr>
<tr>
<td>STUDENT_BEHAVIOUR</td>
<td>All behaviours of student</td>
<td>Explains_how_to_do_that, crossed_arms, started</td>
</tr>
<tr>
<td>STUDENT_COMMUNICATION</td>
<td>Student’s communication</td>
<td>Explains_how_to_do_that</td>
</tr>
<tr>
<td>PROFESSOR_COMMUNICATION</td>
<td>Professor’s communication</td>
<td>Explains_how_to_do_that</td>
</tr>
<tr>
<td>TASK_PERFORMANCE</td>
<td>Student’s task performance</td>
<td>Started, not_started</td>
</tr>
<tr>
<td>P_NAME</td>
<td>Profile attributes</td>
<td>Confused_unclear_behaviour, Defensive_behaviour, Nodding_head, performance_only_to_exact_request, Argumentative_behaviour</td>
</tr>
</tbody>
</table>

Table 11.6. Sorts used
Below, the detailed specification of the leadership support model is explained in terms of LEADSTO specifications (executable temporal rules; cf. [3]). The abstraction process starts with the software agent observing the behaviour of the Ph.D. student and generating a belief about the student’s behaviour. This is shown in rule BS1. Rule BS2 represents the update process of one attribute value. Here, only one rule is given for the update of a certain profile attribute value, in case the Ph.D. student did show a behaviour indicating this profile attribute, otherwise the profile attribute value persists. After all profile attribute values are updated, the software agent calculates the four q-values. The calculation of the q-value for R1 is reflected in rule BS3. Next in rule BS4 the software agent calculates which q-value is highest. The highest q-value is used by the agent in rule BS5 to generate the belief about the development level of the student.

**BS1 Generating a belief on the Ph.D. student’s behaviour from an observation**

If the software agent observes body language BL of STU in a certain context C then the software agent will believe that STU has body language BL in a certain context C.

\[
\text{observation_result(body_language_of_in(BL, STU, C))} \rightarrow \text{belief(body_language_of_in(BL, STU, C))}
\]

**BS2 Analysing the Ph.D. student’s behaviour in terms of profile attribute values**

If the software agent believes that STU has behaviour BL in a certain context C and the software agent believes that body language BL of STU has profile attribute value PVALUE for profile attribute PNAME and the software agent believes that the experience value for BL for profile attribute PNAME is E then the software agent will believe that the profile attribute value of profile attribute PNAME of body language BL of STU is \( \text{ALPHA*PVALUE + (1-ALPHA)*E} \).

\[
\text{belief(body_language_of_in(BL, STU, C))} \& \text{belief(p_values_for_of_in(PNAME, PVALUE, BL, STU))} \& \text{belief(e_value_of_for(E, PNAME, BL))} \rightarrow \text{belief(p_values_for_of_in(PNAME, ALPHA*PVALUE + (1-ALPHA)*E, BL, STU))}
\]
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BS3 Calculating the estimated q-value of R1
If the software agent believes that the first profile attribute PNAME1 of development level R1 has profile attribute value PVALUE1 for STU
and the software agent believes that the second profile attribute PNAME2 of development level R1 has profile attribute value PVALUE2 for STU
... and the software agent believes that the tenth profile attribute PNAME10 of development level R1 has profile attribute value PVALUE10 for STU
then the software agent will believe that the estimated q value of the development level R1 for STU is the average of these 10 PVALUES

belief(highest_value_of_for(PVALUE1, PNAME1, r1, STU)) & belief(highest_value_of_for(PVALUE2, PNAME2, r1, STU)) & ...

→ belief(estimated_qvalue_of((PVALUE1+ PVALUE2+… + PVALUE10)/10, r1, STU))

BS4 Calculating the highest estimated q-value
If the software agent believes that the estimated q-value of development level R1 of STU is X1
and the software agent believes that the estimated q-value of development level R2 of STU is X2
and the software agent believes that the estimated q-value of development level R3 of STU is X3
and the software agent believes that the estimated q-value of development level R4 of STU is X4
then the software agent will believe that the highest estimated q-value for STU is the maximum of X1, X2, X3 and X4

belief(estimated_qvalue_of(X1, r1, STU)) & belief(estimated_qvalue_of(X2, r2, STU)) & belief(estimated_qvalue_of(X3, r3, STU)) & belief(estimated_qvalue_of(X4, r4, STU))

→ belief(highest_estimated_qvalue_of(max(X1,X2,X3,X4), STU) )

BS5 Assessing the development level of the Ph.D. student
If the software agent believes that the estimated q value of development level R1, namely X1, is the highest of the four estimated q-values for STU
then the software agent will assess that the development level of STU in context C is R1

belief(highest_estimated_qvalue_of(X1, STU))

→ assessment(development_level_for_in(R1, STU, C))

After the abstraction process, the next process in Figure 11.2 is the matching process. In the matching process, the software agent generates its desire for the most effective leadership style of the group leader based on the group’s development level. Determining which leadership style is most effective (S1, S2, S3 or S4) is done in [6] by the following straightforward generic matching rule, which has been incorporated in the agent:

If R_i then S_i where i ∈ {1, 2, 3, 4}
Below, rule BS6 models this matching process. In this rule the development level of the student agent is matched with the most effective leadership style of the professor agent.

**BS6 Matching leadership style with development level**
If the software agent assesses that the development level of STU in context C is Ri then the software agent will desire that the leadership style for STU in context C is Si

\[
\text{assessment}(\text{development_level_for_in}(Ri, \text{STU}, C)) \rightarrow \text{desire}(\text{leadership_style_for_in}(Si, \text{STU}, C))
\]

In the refinement process, the software agent determines which leadership behaviours are appropriate in the given context, which it then proposes to the group leader. This is represented in rule BS7 below. The context reflects the history and communication with the student. The software agent has internal knowledge about which behaviours are most effective for which leadership style and in which context.

**BS7 Choosing the appropriate communication response for the professor**
If the software agent desires that the leadership style for STU in context C is Si and the appropriate communication response of PRO is COMM to the behaviour BL of STU in context C then the software agent will propose to PRO to respond with the communication COMM to STU in context C

\[
\text{desire}(\text{leadership_style_for_in}(Si, \text{STU}, C)) \& \text{belief}(\text{comm_response_to_in_for}(\text{COMM}, \text{BL}, C, Si)) \rightarrow \text{proposal}(\text{communication_by_to_in}(\text{COMM}, \text{PRO}, \text{STU}, C))
\]

11.4 Simulation Results
To illustrate the group development support model described above by a concrete example, a specific scenario is addressed. The simulation for the group development level model is discussed in Section 11.4.1. Section 11.4.2 shows the simulation for the support model.

11.4.1 Simulation of the development model
Simulations for an example case have been generated in the LEADSTO software environment [3]. The following example scenario represents a situation in which a Ph.D. student is developing himself in conducting explorative research. In the scenario the student can show behaviours of three types: body language, task performance and communication. These behaviours are indicators of certain profile attributes \( p_{ij} \), which in turn are indicative for one of the four development levels, according to [6].
Before the student agent has decided which behaviour to perform, all possibilities for behaviour that suit the situational context are derived. These are called ‘action_possibilities_student’ in the simulation trace. E.g., there are 7 behaviours possible for the student in the given context ‘c(4)’, see Fig. 10.5 (showing time on the x-axis and state properties on the y-axis).

![Figure 11.5. Simulation trace: action possibilities for student agent](image)

When the behaviour possibilities are derived, only the possible behaviours that match with the student’s current development level are chosen. For example, Figure 11.6 shows that, the development level of the student first is R1 and later R2. The student’s development level can also be derived from the values of $q_i$ which are shown in the graphs in Figure 11.7. This figure shows that from about time point 145, $q_i$ is above the threshold of 0.6. From this time point on the student is in the next development level: R2.

![Figure 11.6. Simulation trace: real development level of the student](image)

![Figure 11.7. Simulation trace: $q_i$ values for R1, R2 and R3 of the student](image)
11.4.2 Simulation of the support process
The software agent analyses the student’s development level and determines the most effective leadership behaviours for the professor. The idea is that the software agent estimates the development level of the student based on his behaviours. After each behaviour of the student, the software agent updates the estimations of the student’s current profile attribute values from which the estimated $q_i$’s are calculated. In Figure 11.8 the updates of the estimated profile attribute values $v_{ij}$ are shown.

![Figure 11.8. Estimated profile attribute values $v_{ij}$](image)

In Figure 11.9 the estimated values of $q_i$ are shown. In contrast, Figure 11.6 showed the real values of $q_i$, but they are identical to the software agent’s estimates in Figure 11.8, only the software agent derives the values at a later time point, since it first needs to observe the behaviours that the student performs. After the software agent has estimated the current development level of the student, it derives appropriate leadership behaviours within the current context and the most effective leadership style.
Part V: Modelling Team and Leadership Dynamics

Figure 11.9. Simulation trace: professor estimates of $q$’s.

Figure 11.10 shows that the input of the software agent’s reasoning component ‘action_selection’ is the belief that the most effective leadership style is S2. Thereafter this component outputs a leadership style behaviour ‘smiling’ which corresponds with the leadership style S2 and with the current context $c(5)$. In Figure 11.11 this leadership behaviour will be outputted by the software agent as a proposal to the team leader. The software agent is called ‘professor_agent’ in the simulation trace.

Figure 11.10. Simulation trace: deriving appropriate leadership behaviour

Figure 11.11. Simulation trace: output of appropriate leadership behaviour

11.5 Discussion
Leadership can be defined as the process of influencing activities of an individual or a group towards goal achievement in a given situation; see, for example, [6, p. 86], [14], [11], [10]. Many informal models on leadership exist these days. However, to our knowledge, no computational models of leadership concerning group or group member development exists yet. This
chapter presents a first exploration into computational modelling of such a leadership model. The development model from the situational leadership theory in [6] was chosen as the basis for the support model. This model was chosen because it focuses on the behaviour of the group or group member and because the integration of the effectiveness dimension makes it possible to predict the effectiveness of the different leadership styles in the specific situational context or situational demands.

An agent-based approach to formalise and simulate group development and leadership support was chosen; e.g., [3], [1], [2]. Simulations of an example scenario of a Ph.D. student developing his skills in conducting explorative research, showed that the model is able to show how the student develops from one development level to another. The simulations also showed how the support model is able to estimate the group development level and to derive the appropriate behaviours for the group leader.

As a next step, various extensions of the support model will be explored. For example, the concept of context, which reflects the history and communication between team leader and the group (member) can be modelled in more detail. Furthermore there is the possibility that the software agent does not estimate the group development correctly. In that case, a possibility could be that the software agent is able to learn from its errors by adapting the parameters by which it estimates the development level.

A more extensive external validation of the model is also part of future work, although the model is based on the situational leadership theory in [6], which itself has been validated empirically. The idea is to develop a software agent that is able to monitor the development of a team or individual in a particular environment (e.g., operators on a naval vessel, employees in an organisation, or a sports team), and to provide support to the leader in the form of behaviour proposals. For this, the software agent should be able to observe and interpret body language, communication and task performance.

References
Part V: Modelling Team and Leadership Dynamics


Chapter 12 - Crisis Management Evaluation: Formalisation & Analysis of Communication during Fire Incident in Amsterdam Airport Train Tunnel

Kees Boersma, Julienka Mollee, David Passenier, C. Natalie van der Wal

Abstract. Communication in crisis management is important for all processes and can lead to a fast and effective ending of a crisis. In this chapter, a public inquiry report of the real world incident “fire in the Amsterdam Airport Schiphol train tunnel” was formalised and analysed by automatic property checking. It is shown how this approach is a convenient and effective manner to analyse crisis management and to evaluate what went wrong, where and when.

This chapter will appear as:
12.1 Introduction

Fast and effective emergency response is crucial for public safety in critical areas such as tunnels, but the coordination to realise this often fails. In the rare event of a crisis, various parties must be prepared to react in a timely, coordinated manner, which often does not occur. Crisis coordination problems are an international phenomenon. The catastrophic effects of Hurricane Katrina, that hit New Orleans in 2005, showed how fragmented distribution of new information impaired speedy response and how ineffective communication between disciplines incapacitated coherent decision making [1], [2]. The disaster Hurricane Katrina became iconic because of its scale, but similar problems with crisis coordination occurred during smaller incidents. For example, the crash of a Turkish Airline Boeing 737-800 near Schiphol Amsterdam on 25 February 2009, revealed the problematic communication routines of the first responders [3]. These cases illustrate that improved coordination strategies are needed. In the Netherlands, like in other countries, emergency services – fire fighters, police and medical services – are attempting to learn from failures in previous experience during incidents and accidents.

Rigid command and control structures currently in place cannot adapt quickly enough to the unpredictable events as they unfold. Research suggests that the military concept of Network-Centric Capabilities (NCC) could fulfil this need [4], [5], [6]. These capabilities authorize first responders to decide faster, supported by communication systems that enable shared situational awareness [7], [8]. In order to implement NCC and improve emergency response, coordination processes during crises must be better understood. Methods to analyse crises, however, are costly and time intensive.

This chapter shows how a formal analysis, using automatic property checking, can provide a more efficient and practical method to study crisis coordination processes. The case to illustrate this method is a dangerous fire incident that occurred on July 2nd 2009 in the train tunnel and underground train station of Amsterdam Airport Schiphol. Different modalities of crisis management could be studied by formal analysis, such as the beliefs and intentions of those involved. The current research focuses on actions and communications, because by using data from a public inquiry report [9], actions and communications are the most accessible and they are essential to the emergency response problem. Communications relay information that must be shared timely and spread coherently in the overall network of involved parties. Furthermore, they are more reliable than beliefs and intentions, which are not clearly stated in the report.

Our research question is: How can automatic property checking be used in the formal analysis of coordination problems occurring in emergency response during crises? This question is answered by showing how our method indicates
the measure of success of several key coordination features. These features refer to the time of response, disciplinary boundaries, and the quality of information sharing in the overall network. Emergency response must be effective in a short, specified period of time after the fire hazard arises. Information must be spread quickly across disciplinary boundaries to facilitate a common operational picture. Overall, the information network must support quick and effective decision making, where for example urgent requests prompt quick and adequate reactions.

The chapter proceeds as follows. In Section 12.2, the Schiphol train tunnel fire case is briefly described on the basis of the public inquiry report [9]. Section 12.3 details the formalisation process and the resulting formal trace. Section 12.4 explains the automatic property checking and its results. In the final section, we conclude what value this method has in the field of crisis management research.

12. 2 Schiphol Tunnel Fire
On July 2nd, 2009, an incident took place in the Schiphol train tunnel and station. Around 5:25 PM, dirt collecting in an open case just next to a railway track containing electrical wires began to smoulder, due to a spark released by the braking wheels of a passing train. The case was located in one of the two adjacent tubes on the side of Amsterdam city. Alarm calls went to the Schiphol Coordination Centre that was quick to mobilize airport fire and medical services. The remotely operating Railway Traffic Controller (RTC) also received reports about smoke from train conductors passing through the station, but was hesitant to declare an emergency. When signals and switches began to malfunction, three trains halted in the tunnel tube where the fire was, because of standard procedures in case of such malfunctions. A ‘disturbance’ emergency scenario was declared by the RTC and his back office. Coordination between the railway and emergency services occurred mostly through the railway Emergency Operations Coordinator (EOC) and the Airport Fire Officer (AFO). As a result of miscommunication, the three trains in the tunnel had to hold for over thirty minutes with increasingly anxious passengers [9]. The AFO asked the regional dispatch room to relay to the Emergency Operations Director (EOD) a request to drive the trains out of the tunnel. This would create a safe space for the fire brigade, holding on the station’s platform, to enter the tunnel and find the fire. Instead, the EOD asked the RTC to hold the trains where they were, because he thought the fire fighters were already in the tunnel. The exploring fire fighter crews, who could not find the origin of the fire, were surprised to find the trains standing in the tunnel. They asked for their immediate departure at 6:00 PM through their commanding AFO. He relayed this to the EOC, who was initially unable to
pass the order through to the RTC, as he was on the phone with the technical department and had no additional phone lines. After receiving the message, starting at 6:05 PM the RTC ordered the trains out one by one, which took 15 minutes to complete. The fire had already died out by itself, and had not posed a real threat. Yet it had taken far longer than the critical 15 minutes to secure a safe evacuation of the passengers or to find and control the fire.

12.3 Formalisation of Crisis Management Communication
In this section, the process of formalising the available data is addressed. First, the goal and content of the report, from which the data on the calamity in the Schiphol tunnel was extracted, is discussed. Then, the formalisation process and the resulting formal trace of the course of events are described.

12.3.1 The Report
The public inquiry report on the calamity in the Schiphol tunnel [9] served as a basis for the analysis of the coordination problems during the emergency response. The investigation is reported for a dual reason: to inform the citizenry on the response to incidents in the public domain, and to advise organisations on measures to prevent similar incidents in the future.

The report consists of several parts. First, factual information on the location, cause and risks of the fire incident is provided. For example, an estimation of the number of passengers that were stuck in the tunnel is provided, and the extent to which the Schiphol train tunnel meets the safety standards is assessed. In addition, an overview of the involved organisations and services and their responsibilities is included, together with a brief description of relevant procedures and protocols. Second, the course of events is described from different perspectives, namely from the perspective of ProRail, the Dutch organisation for maintenance of the national railway network infrastructure, the perspective of the Nationale Spoorwegen (NS), the Dutch principal passenger railway operator, and from the perspective of the three main emergency services the police, fire fighters and medical services. These descriptions were also summarised in a table with a chronology of the most important events. (See Figure 12.1 for a fragment of this timeline.) Also, summaries of interviews with people from various organisations involved with the emergency response are provided. By this means, the adequacy of the response of each of the involved parties can be analysed and evaluated separately.
In the formalisation process, the three descriptions of the events during the calamity and the condensed timeline were used to extract the locations, actions and communications of the parties involved. Additionally, screenshots of the screens available to the railway traffic controller were used to determine the locations of the trains inside the tunnel tubes and alongside the platforms at the Schiphol train station.

12.3.2 Formalisation
In order to be able to check properties of the emergency response to the incident automatically, first a formal trace must be constructed. This process of formalising the textual description of the events into a computer-readable format equates translating the highly qualitative data into a combination of temporal logical and numerical statements [11]. In order to do so, the relevant actors, locations and concepts must be identified, and correspondingly an ontology should be specified. A partial specification of this domain ontology is provided in Table 12.1.

The main concepts used to formally describe the emergency response to the incident are *world states*, *observations* of information elements by agents, *communications* of information elements by agents to agents, and *actions* by agents. The world states include the locations of actors, the occurrences of signal and railroad switch malfunctions, and the belongs-to relations between actors and organisations. The observations state the information elements that agents perceived, and the communications state how one agent shared a certain information element with another agent. These communicated information
elements concern, for example, locations of signs of fire, intentions for actions, requests for information, permission for actions, approvals of permissions, or isolated fragments of information, such as the fact that passengers are panicking or that the fire source is not found yet. Correspondingly, the actions concern, for example, entering and exploring the tunnel tubes by the fire fighter teams, evacuating the platforms, converting the trains in the tunnel tubes and vacating the tunnel.

Table 12.1. Partial specification of the domain ontology

<table>
<thead>
<tr>
<th>Predicate</th>
<th>Informal meaning</th>
</tr>
</thead>
<tbody>
<tr>
<td>world_state(I:INFO)</td>
<td>The information element I holds in the world.</td>
</tr>
<tr>
<td>observation(A:AGENT, I:INFO)</td>
<td>Agent A observes information element I.</td>
</tr>
<tr>
<td>communication_from_to(A:AGENT, B:AGENT, I:INFO)</td>
<td>Agent A communicates information element I to agent B.</td>
</tr>
<tr>
<td>performed(A:AGENT, ACT:ACTION)</td>
<td>Agent A performs action ACT.</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Sort</th>
<th>Elements</th>
</tr>
</thead>
<tbody>
<tr>
<td>AGENT</td>
<td>{RTC1, RTC2, CT756, CT3558, AFO, Schiphol_employee, CCS,…}</td>
</tr>
<tr>
<td>ORGANISATION</td>
<td>{ProRail, NS, Schiphol, FireFighters, Medics, Police, RMP, …}</td>
</tr>
<tr>
<td>LOCATION</td>
<td>{tunnel1A, tunnel2A, platform12, platform34, Schiphol_station, …}</td>
</tr>
<tr>
<td>ACTION</td>
<td>{dispatch_to(L:LOCATION), evacuate(L:LOCATION), convert_train…}</td>
</tr>
<tr>
<td>INFORMATION ELEMENT</td>
<td>{at_location(weak_signs_of_fire,platform34), request(info(situation), request(permission(enter(tunnel))), request(action(stop_train)), permission(vacate_tunnel), sign_clear(firefighters), panic_in_train, fire_source_not_found, …}</td>
</tr>
</tbody>
</table>

Using the ontology depicted in Table 12.1, the response to the Schiphol train tunnel incident was formalised in the software tool based on the language Leadsto [10]. This language is an extension of order-sorted predicate logic that allows for representation of both quantitative and logical data. Figure 12.2 is a screenshot of a fragment of the resulting trace, and Figure 12.3 shows the corresponding visualisation, where the presence of a blue bar indicates that the statement is true at the corresponding time point. Each time interval in the trace represents half a minute.
12.4 Automatic Property Checking

This section addresses the analysis of the empirical trace of the fire incident in the Schiphol tunnel, by specification and verification of a number of dynamic properties that have been identified and formalized in the Temporal Trace Language (TTL) and were automatically checked \[11\]. Via a software tool based on TTL, the researcher can check whether certain expected (dynamic) properties, expressed as statements in the TTL, hold for a given trace (defined as a time-indexed sequence of states). The purpose of checking the trace for these dynamic properties is to automatically check if important characteristics of net centric incident management hold in the empirical trace and if mistakes were made in communications and actions. This analysis is an innovative way to check for mistakes or find important characteristics of behaviour in the empirical data that is available during or after crisis management.

The TTL software environment includes a dedicated editor supporting specification of dynamic properties to obtain a formally represented temporal predicate logical language TTL formula. In addition, an automated checker is included that takes such a formula and a set of traces as input, and verifies automatically whether the formula holds for the traces. The language TTL is built on atoms referring to states of the world, time points and traces. In addition, dynamic properties are temporal predicate logic statements, that can be formulated with respect to traces based on a state ontology.

Below, a number of the dynamic properties that were identified for the empirical trace of the fire incident in the Schiphol tunnel are introduced, both in semi-formal and informal notation (where state(\(\gamma\), \(t\)) \(\models\) \(p\) denotes that \(p\) holds in trace \(\gamma\) at time \(t\)). Following every property, an evaluation on the empirical trace is discussed. See \[11\] for more technical details.
P1a – Fire_Under_Control_Within_15_Minutes

For all time points t1 and t2, all AGENTS a and b in trace γ, if at t1 there is a fire at location tunnel 2A and there is no earlier time point at which there is a fire at location tunnel 2A, and at t2 ≥ t1, AGENT a communicates to AGENT b that the fire is under control, then interval i = t2 - t1 and i ≤ 30.

Property P1a can be used to check whether the fire was under control within 15 minutes. This is important to check, because as long as it is not clear if it is a big fire or a small (self stopping) fire, the evacuation should be the first priority, in order to save as many lives as possible. The result of checking this property in the TTL tool is that this property does not hold in the trace; a time gap of 125 intervals = 62.5 minutes was found between the start of the fire and the communication that the fire was under control.

P1b – Evacuation_Performed_within_15_Minutes_At_Fire_Location

For all time points t1 and t2, all AGENTS a and b in trace γ, if at t1 there is a fire at location tunnel 2A and there is no earlier time point at which there is a fire at location tunnel 2A, and at t2 ≥ t1, AGENT a communicates to AGENT b that the tunnel is clear of trains, then interval i = t2 - t1 and i ≤ 30.

This property can be used to check whether the evacuation of the tunnel (fire location) was performed within 15 minutes. This property was not satisfied in the trace, because the time between the start of the fire and the evacuation of the tunnel was 55.5 minutes, since interval i = 111 time steps.
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P2a – Communications Between Organisations
At time point t1 in trace $\gamma$, AGENT a communicates to another AGENT b INFO_ELEMENT k, and agent a belongs to an ORGANISATION $o_1$ and agent b belongs to an ORGANISATION $o_2$, and $o_1 \neq o_2$.

$$P2a_{\text{COMMUNICATIONS\_BETWEEN\_ORGANISATIONS}}(\gamma:\text{TRACE}, t1:\text{TIME}, a, b: \text{AGENT}, k: \text{INFO\_ELEMENT}) \equiv \exists o_1, o_2: \text{ORGANISATION} \text{ state}(\gamma, t1) \models \text{communication\_from\_to}(a, b, k) \& \text{state}(\gamma, t1) \models \text{world\_state}(\text{belongs\_to}(a, o_1)) \& \text{state}(\gamma, t1) \models \text{world\_state}(\text{belongs\_to}(b, o_2)) \& o_1 \neq o_2$$

P2b – Sum Communications Between Organisations
For all traces $\gamma$, time i, AGENT a and b and INFO_ELEMENT k, every time P2a holds, add 1 to the sum that starts with 0.

$$\forall \gamma, I, a, b, k \exists n: \sum_{i=0}^{n} \text{case}( p2b_{\text{COMMUNICATIONS\_BETWEEN\_ORGANISATION}}(\gamma, i, a, b, k), 1, 0) = n$$

P2c – Communications Within Organisations
At time point t1 in trace $\gamma$, AGENT a communicates INFO_ELEMENT k to another AGENT b, and agent a belongs to an ORGANISATION $o_1$ and agent b belongs to an ORGANISATION $o_2$, and $o_1 = o_2$.

$$P2c_{\text{COMMUNICATIONS\_WITHIN\_ORGANISATIONS}}(\gamma:\text{TRACE}, t1:\text{TIME}, a, b: \text{AGENT}, k: \text{INFO\_ELEMENT}) \equiv \exists o_1, o_2: \text{ORGANISATION} \text{ state}(\gamma, t1) \models \text{communication\_from\_to}(a, b, k) \& \text{state}(\gamma, t1) \models \text{world\_state}(\text{belongs\_to}(a, o_1)) \& \text{state}(\gamma, t1) \models \text{world\_state}(\text{belongs\_to}(b, o_2)) \& o_1 = o_2$$

P2d – Sum Communications Within Organisations
For all trace $\gamma$, time i, AGENT a and b, every time P2c holds, add 1 to the sum that starts with 0.

$$\forall \gamma, I, a, b, k \exists n: \sum_{i=0}^{n} \text{case}( p2c_{\text{COMMUNICATIONS\_WITHIN\_ORGANISATION}}(\gamma, i, a, b, k), 1, 0) = n$$

Properties P2a and P2c check whether there exists a certain communication k between agent a and b. Properties P2b and P2d, respectively count the number of times P2a or P2c hold in the trace. This way, the number of times that there are communications between agents of different organizations and of the same organization, are counted. This is useful information, because the ratio can give an insight in the quality of information sharing between organisations – one of the characteristics of a net centric approach to incident management. The result for the Schiphol trace is that there are 120 communications between organizations and 103 communications within organizations.
**P3a – Time Between Request Permission And Permission To Enter Tunnel 1A**

For all time points $t_1$ and $t_2$ and all AGENTS $a$ and $b$ in trace $\gamma$, if at $t_1$ agent $a$ requests to enter tunnel $1A_north$ to agent $b$ and at time point $t_2 > t_1$ agent $b$ communicates a permission to enter tunnel $1A_north$ to agent $a$, then interval $i = t_2 - t_1$.

$$P3a\_TIME\_BETWEEN\_REQUEST\_PERMISSION\_AND\_PERMISSION\_TO\_ENTER\_TUNNEL1A \equiv$$

$$\forall \gamma: TRACE, \forall t_1, t_2: INTEGER, \forall a, b: AGENT$$

$$state(\gamma, t_1) \models \text{communication_from_to}(a, b, \text{request}(\text{permission(enter(tunnel1A_north)))) \land$$

$$state(\gamma, t_2) \models \text{communication_from_to}(b, a, \text{permission(enter(tunnel1A_north))) \land}$$

$$t_1 < t_2 \Rightarrow$$

$$\exists i: \text{interval}$$

$$i = t_2 - t_1$$

**P3b – Time Between Request Permission And Permission To Vacate Tunnel**

For all time points $t_1$ and $t_2$ AND ALL agents $a$ and $b$ in trace $\gamma$, if at $t_1$ agent $a$ requests a permission to vacate the tunnel to agent $b$ and at time point $t_2 > t_1$ agent $b$ communicates a permission to vacate the tunnel to agent $a$, then interval $i = t_2 - t_1$.

$$P3b\_TIME\_BETWEEN\_REQUEST\_PERMISSION\_AND\_PERMISSION\_TO\_VACATE\_TUNNEL \equiv$$

$$\forall \gamma: TRACE, \exists t_1, t_2: INTEGER, \forall a, b: AGENT$$

$$state(\gamma, t_1) \models \text{communication_from_to}(a, b, \text{request}(\text{permission(vacate_tunnel)))) \land$$

$$state(\gamma, t_2) \models \text{communication_from_to}(b, a, \text{permission(vacate_tunnel))) \land}$$

$$t_1 < t_2 \Rightarrow$$

$$\exists i: \text{interval}$$

$$i = t_2 - t_1$$

The properties P3a and P3b check how much time there is between a request for permission and the permission. Properties P3a1 holds for 1 time step = 30 seconds and P3b holds for 14 time steps = 7 minutes.

In sum, automatic property checking indicated that the fire was not under control within 15 minutes and that the evacuation was not performed on the correct fire location within 15 minutes. These results show that the fire incident was a near miss situation: if the fire would not have gone out by itself, people stuck in the trains in tunnel 2A could have died. Furthermore, there were more communications between organizations than within organizations in our trace. However, the communications within organizations were partially neglected, because these organizations were black-boxed in the report. Therefore, one should be cautious to draw conclusions upon these numbers.

With regard to the permissions, one can see that the permission to evacuate the tunnel was relatively time expensive, due to the fact that this was a next step in the whole procedure, whereas the decision to enter the tunnel already was part of the action and followed immediately after the request.
12.5 Discussion
The goal of this chapter was to show how automatic property checking can be a more efficient and practical method to study crisis coordination processes. Communications and actions during the fire incident that occurred on July 2nd 2009 in the train tunnel and underground train station of Amsterdam Airport Schiphol were analysed. Although this fire turned out to be harmless, the organisations involved in the emergency response proved to be ill-prepared for a serious fire that could occur in any tunnel. A serious, explosively growing tunnel fire can be lethal within 15 minutes. Automatic property checking showed that fire was not under control on time and that the evacuation was not performed within 15 minutes on the exact fire location and the permission to evacuate the tunnel was relatively time expensive.

Overall, according to a net centric approach, the information network must support quick and effective decision making, where for example urgent requests prompt quick and adequate reactions. Understanding critical communication processes can then assist in simulating and providing advice about more effective communication strategies that meet currently unfulfilled needs in both practice and research. Research is predominantly focussed on organisational structures, but decision making in crises occurs ad-hoc and under conditions of significant chaos. In such situations, adaptive communication strategies are needed. Current procedures specify rigid communication links within organisational disciplines, where only higher ranking officials coordinate between the parties involved. In practice, this leads to a fragmented spreading of information in the network of people involved in the crisis response. Information travels along lengthy, inefficient communication chains. New information, including requests and permissions to take urgent actions, takes long to travel and often goes lost. The properties in our analysis were designed to indicate where in the formal trace of the events these processes succeed or require the development of alternative communication strategies drawing on NCC. The results show where in the trace of events the communication went wrong and indicate that there is room for improvement, namely following a more net centric communication strategy.

Although the current research shows that automatic property checking can be a more efficient and practical method to study crisis coordination processes, the current formalisation process still requires a lot of hours work. Part of future work is to make this process automated to save time. Other future work concerns planned comparisons of the formalised data of the Schiphol fire incident with agent-based simulations according to a more net centric approach. The (dynamic) properties from Section 12.4, amongst others, can then be used again. Since the TTL tool can take both simulated and
empirical traces as input, it can be used to check (automatically) whether the
generated simulation runs show similar patterns to the real world transcripts.

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Part VI: Discussion

Abstract. In Part VI, the results of the research reported in this book are summarised and their implications are stated. Ideas and plans for future work based on this thesis are presented.
Chapter 13: Discussion

The goal of this research was to analyse and design agent-based support models for teams integrating social interaction processes with internal processes, involving both affective and cognitive aspects. The models proposed and analysed were aimed to be innovative and justified by scientific domain knowledge, and thus extending research in computational modelling, where such processes usually are modelled separately.

The main research question was: how can an intelligent agent-based system be designed, that gives support to teams, based on their social interactions and internal processes? The scope of the main question as used in the research reported here is very general and broad: different domains were explored, such as group emotion, informal caregiving, group development, crisis management and group evacuation. Since group behaviour is very complex and the integration of internal processes and social interactions needs careful analysis, the main question was differentiated into a number of more specific sub-questions. Different parts of this thesis address different sub-questions. Below, first the results are summarised. Next, the implications and limitations of this research are discussed. Then, new questions for future research are proposed.

13.1 Results

The general approach towards addressing the main research question was to first explore agent-based modelling of individual and social human processes within specific domains. Next, ways were explored to model interactions between social and internal human processes involving both affective and cognitive elements, and to integrate different agent-based models addressing these into one new model. Then, the design of support models was explored based on the integrated agent-based models. Finally, the models were applied to specific case studies and evaluated by simulations, experiments and automatic checking of emerging properties. To accommodate these different steps that had to be taken, the main research question was differentiated into seven sub-questions:

1. How can social interaction processes be modelled using an agent-based approach?
2. How can an intelligent agent support social interaction processes in a team?
3. How can social interaction processes be integrated with individual internal processes in agent-based models?
4. How can affective processes and cognitive processes be integrated in agent-based models?
5. How can support for groups, based on internal processes and social interactions, be modelled with an agent-based approach?
(6) Do the models simulate the real world process or phenomena known from the scientific literature correctly?

(7) Do the models perform better than other similar models addressing the same?

The answers to these questions will be discussed per part. Table 13.1 shows which questions were answered in which Part(s) and Chapter(s).

Table 23.1 Answered research questions per chapter and part

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13.1.1 Results Part II

In Part II questions 1, 2, 6 and 7 are addressed in the domain of emotion contagion and recognition. In Chapter 2, agent-based models of emotion contagion were proposed and explored, where emotions could interact socially in an amplifying or absorbing manner, or in a combination of these two. A heuristic support model was proposed, in which an artificial agent can give advice to a team leader on how to keep the group emotion positive. This chapter proposes one of the first agent-based models that models group emotion and is a stepping stone towards the models in Part III, where social interactions were integrated with internal processes. Chapter 3 describes the psychological experiment which tested if emotions have an effect on a person’s thought action repertoire, creativity and memory. No effect of emotions on the thought action repertoire or creativity was found. The only confirmation of the broaden-and-build theory was found in the domain of memory, where negative emotions decreased the gist and central aspects of memory and positive
emotions increased central and background aspects of memory, both in comparison to a neutral state. The modest support for the broaden-and-build theory requires more experiments to find out if Frederickson’s results really exist in the world. In Chapter 4, a model that recognises emotions in the human voice was designed, based on the Random Forest algorithm. The model can recognise if a certain emotion goes up or down in its intensity and can estimate the extent of this change. The model performed better than baseline, which was the random majority guess. Furthermore, the model performed better than humans. This was shown through a controlled experiment, in which humans performed the same task as the computational model. This model is envisioned to be built into a mobile phone to prevent depression in humans by monitoring the human mood, by analysing his/her voice. The first steps were taken towards this envisioned intelligent agent.

13.1.2 Results Part III
In Part III, questions 3, 4, 5, 6 and 7 are addressed. Agent-based models that integrate social and internal dynamics were designed and analysed in this part. In Chapter 5, the focus was on how intentions, beliefs, and emotions of individuals in a group affect each other. For example, intention and emotion contagion (through social interactions) was integrated with emotion-related valuing of intentions (internal process). Different simulation experiments showed how the interactions work in groups that have to decide which way to go in an evacuation scenario. Chapter 5 was a stepping stone towards the work in Chapter 6, where the agent-based model was extended with actions (walking in a certain direction with a certain speed). In this chapter, the agent-based model AScribe (Agent-based Social Contagion Regarding Intentions Beliefs and Emotions) was introduced and applied to a real life incident where a panicked crowd ran away from Dam Square on the 4th of May and people got injured. The parameters of the agent-based model were automatically tuned to the specific case and the positions and walking directions of the Amsterdam crowd were compared to the corresponding representations in AScribe. Distances between the real positions and the simulated positions were fairly small. Furthermore, four models applied to the 4th of May incident were compared: one baseline model where all agents stand still, two variants of the model AScribe (with and without contagion of mental states) and an implementation of a model proposed by Helbing and colleagues. AScribe with contagion outperformed the other models: it resulted in the smallest errors. Also, statistical analysis showed that the 4 models differ significantly from each other. Moreover, other researchers have compared a simpler version of the model AScribe (limiting themselves to emotion contagion and proximity effects) to an epidemiological model and an agent-based model.
named ESCAPES. Each of these models addresses fear contagion differently. The models were applied to a panicked crowd evacuation scenario, the Amsterdam 4th of May case and a protest incident in Greece. Also in this evaluation study ASCRIBE outperformed the other models by producing, again, the smallest errors. These results show that the underlying mechanisms in the model ASCRIBE are well suited for evacuation scenario’s where emotions, proximity effects and beliefs and intentions all have on influence on the crowd behaviour. In Chapter 7, the model ASCRIBE was applied to another real life emergency scenario, namely that of the 7-7 London bombings. In this scenario, ASCRIBE modelled the contagion of fear, intentions and beliefs and the relations between and amongst them. First, survivor statements for formalised to create an empirical simulation trace. Next, ASCRIBE was applied to the scenario and simulated. Then the empirical simulation trace was compared to the ASCRIBE simulation trace and an automatic formal check on both simulation traces was performed. Results show that the model ASCRIBE can reproduce similar patterns in the emotions and actions of the persons during the 7-7 London bombings.

13.1.3 Results Part IV
In Part IV, questions 3, 4, 5 and 6 are addressed. In Chapter 8 and 9, internal processes concerning coping and stress buffering, and social interactions of informal caregivers and the patient they take care of were integrated. From psychological, social and emotion theories, the most important concepts belonging to the mechanism of stress in the informal caregiver and the care recipient were extracted and modelled. The proposed model can simulate how the dynamics of long term stress, short term stress and stress buffering develop in the informal caregiver and care recipient during negative events. The patterns the model provides were verified by checking if important properties put forward in the literature indeed emerge from the model. This was done by checking whether they hold in the simulation traces and by analysing the equilibriums the model provides, through mathematical analysis. Chapter 8 was a stepping stone towards Chapter 9; in Chapter 8 the domain of informal care giving was explored, and in Chapter 9 the scope was extended by exploring an artificial support agent that supports informal caregivers, based on their internal processes (like coping and stress buffering) and social interactions (like care giving). Through model-based reasoning, the agent can monitor the caregiver’s health and, if necessary, generate support actions: for example, teaching the caregiver to manage stress or how to apply problem-focused coping, and give feedback or teaching the caregiver how to take care of him/herself emotionally, mentally or physically.
Chapter 8 was also a stepping stone towards Chapter 10; Chapter 10 extends the negative mood contagion addressed in Chapter 8 (social and affective process) with the integration of an internal process involving cognitive and affective aspects: emotion regulation. Different emotion regulation strategies were formalised and integrated with negative mood contagion. Simulation experiments show that the model can produce interesting patterns that illustrate the combined effect of emotion regulation and emotion contagion. By mathematical analysis equilibria of this model were identified.

13.1.4 Results Part V
In Part V, questions 1 and 2 are addressed in the domain of leadership. In Chapter 11, with Situational Leadership Theory as a point of departure, the mechanisms of group development were explored as well as an artificial agent that can support a team leader in choosing the correct leader style behaviours according to the group’s development level. The models were illustrated for the social interactions between a professor and his or her students. The model can predict the effectiveness of each leadership style on the development of the group and its members. The development of group members and leadership support were simulated in an example scenario, in which a Ph.D. student is developing skills in conducting explorative research. The results show that the model is able to estimate the personal development level of the simulated Ph.D. student and to derive and communicate appropriate behaviours to the professor.

Chapter 12 is a stepping stone towards designing an agent-based model that can simulate the communication between different organisations during crisis management. The communications about the fire in the Amsterdam Airport Schiphol train tunnel were extracted from a public inquiry report and formalised into an empirical trace. Automatic property checking was performed on the empirical trace, addressing, for example, whether the fire was under control on time and evacuation was performed within a prescribed time frame (in both cases with a negative outcome). Such an analysis by automatic property checking was shown to be an efficient and practical method to study crisis management.

13.2 Implications, strengths and limitations of the current research
The implications of the current research for the field of computational modelling are first of all, that it provides and extends knowledge on how to analyse and design new, innovative computational models for human processes integrating social and individual internal functioning and involving both
cognitive and affective elements. The explored and proposed models are
innovative in two ways. Firstly, they address the integration of human
processes and aspects (individual and social, cognitive and affective) that
usually are modelled separately. The explored models integrate internal
processes, like coping, emotion regulation and emotion-related valuing, with
social interactions, for example, underlying care giving, emotion contagion and
emergence of collective intentions. Typically these processes are not modelled
all together within the same model. For example, traditional crowd models like
that of Helbing and colleagues [9], [10] can also model escape routes of
crowds, based on intentions, but does not use emotion contagion and intention
contagion between the crowd members. The model of Helbing and colleagues
is based on a general force model. The model assumes that each agent likes to
move in a certain direction with a certain desired velocity. In addition, the
agent is influenced by certain interaction forces: it wants to keep a certain
distance from other agents and walls. In [5] the model of [9] is extended by
adding individual characteristics to agents, such as the need for help and family
membership. In both models, there are no individual emotion, belief and
intention states that play a role. In contrast, in [15] an agent has an
‘emotional_status’, which determines whether agents walk together (i.e. it
influences group formation). The emotional status of an agent can change
when two agents meet. An even further elaborated role of emotional and
psychological aspects in a crowd behaviour model can be found in [20]. In this
model, several psychological aspects influence the decision making of
individual agents, for example, motivation, stress, coping, personality and
culture. In none of the other computational models, there is contagion of
emotional or other mental states between people, as in the proposed models of
this thesis. Furthermore, there are BDI-models that integrate emotions as well,
see for example [18, 12]. In these models affective and cognitive aspects are
integrated, but not yet extended with social interactions, like in the current
work. Moreover, most existing computational models of emotional processes
represent emotion as a process or state that depends on observed stimuli by a
single agent; e.g., [7], [14], [20]. These models of emotion differ from the
proposed models in this thesis, in that the focus in these models lies more on
individual emotions, not on collective emotion. Another difference can be
found the social contagion in the proposed models and similar computational
models called social diffusion models.[19], [10], [16] Most social diffusion
models follow the diffusion of innovations model of Rogers, in which it is
posed that the diffusion process of innovations proceeds in the form of an S-
shaped curve: the contagion of an innovation starts slow, but then accelerates
rapidly, followed by a rapid deceleration [19]. Even though social diffusion
models can simulate the contagion of a certain innovation and use similar
concepts as the current proposed models, such as a sender, receiver and communication channel, these computational models of social diffusion differ from the proposed models, in the way that they model the complex spread of innovations as diffusion that is asymmetric in time, irreversible, and nondeterministic. The models in this thesis, models the continuous spread of emotions, intentions and beliefs among the group members over time, which can have many patterns in it and are reversible in time.

Secondly, the proposed models in this thesis explore new domains that are not or hardly touched upon by other computational modellers, like group emotion support, support models of care giving interactions and team support based on the group’s development level. For example, some applications have been proposed to support persons with a depression (e.g.[2]), but automated support for caregivers has not been addressed yet. The integration addressed is a complicated process and the obtained knowledge can give ideas to other researchers and insight in how to do it. Also, the current approach shows other researchers the advantages of hybrid modelling (the combination of qualitative and quantitative models), like more insight into the dynamics of the phenomenon that is modelled, and more possibilities of analysis.

A more specific implication of the current work lies in the development and validation of the model ASCRIBE. This model was designed based on state-of-the-art theories about collective human decision making processes, and the role of emotions and social interaction in these processes. More specifically, recent (informal) theories from the relatively new disciplines Cognitive and Social Neuroscience are at the basis of this model. Moreover, the model ASCRIBE was validated against the empirical simulation traces of real life evacuation scenario’s known as the Amsterdam 4\textsuperscript{th} of May case and the 7-7 London Bombings. Whenever a model is validated, it can show other researchers that it is a useful model to use, or to further validate. Other researchers have picked up ASCRIBE and tested it against other crowd behaviour models. This shows how the enterprise of computational modelling in general proceeds: creating new models, validating them, communicating the results to other researchers that can use the model for further research like comparing the performance to other models or to use the model in a certain domain.

The strength of the current approach is that the models are generic: they can be applied to different domains relatively easily and are easy to implement in any computer language. For example, the model ASCRIBE was shown to be applicable to the 4\textsuperscript{th} of May incident and the 7-7 London Bombings. The emotion contagion model was applied to simulate positive and negative mood contagion in general teams that work in offices, like in Chapters 2 an 11, but also integrated in models that simulate crowds that are panicking, in Chapters
5, 6, 7, or models that simulate the care giving interactions and internal processes of informal caregivers of a depressed person, in Chapters 8, 9. A specific strength in these domains is that they are innovative in integrating social interactions with internal processes relevant for these domains. For example, no other crowd behaviour models have integrated the internal beliefs, intentions and emotions of individual person’s in crowds and their effects internally and in the social interactions of the crowd. Furthermore, the modelling approach and languages used in the proposed models (TTL and LEADSTO, see [4] and [3]) allow the users to specify new ontologies themselves. This distinguishes the used modelling approach from more specific approaches that are developed especially for modelling cognition, e.g. ACT-R [1], SOAR [13] and COGENT [6]. These architectures consist of a number of different modules that reflect specific parts of cognition, such as memory, rule-based processes and communication. They are hybrid approaches, like TTL and LEADSTO, supporting both quantitative and qualitative relations. However, in LEADSTO and TTL, the qualitative and quantitative aspects can be combined in the same expressions, whereas in ACT-R, SOAR and COGENT separate modules exist to express them. Another exclusive feature of TTL and LEADSTO is the logical foundation of these languages.

A limitation of any computational model is that being a model it is always a simplification of the real world.Choices have to be made on which aspects of the real world phenomenon will be modelled and which not. A related limitation is that one always has to make modelling assumptions; like that emotion level can be modelled as a number in the interval [0, 1]. Specific limitations of the current work are for example the limitation of the emotion contagion model in Chapter 2, where only one emotion at a time is simulated. It can easily be applied to multiple emotions at the same time as long as no mutual interactions between different types of emotions are assumed. Specific interactions between different emotions such as the impact of aggression on anxiety were left out of the scope of the research reported here. Another limitation of the research described concerns validation. Validation processes require a lot of hours of work. For example, to compare the ASCRIBE simulation trace with the actual walking patterns of the Amsterdam crowd, many hours were put into annotating the walking patterns from the Amsterdam crowd from video and tuning the parameters of the model to this specific case study. A second difficult step in such a validation process is to choose how to assess the model: by which measure? For example, in Chapter 6 the walking patterns were chosen to indirectly validate the contagion of mental states in ASCRIBE. Direct validation of the contagion of the mental states would be a further contribution to the overall validation of the model. But
then one would have to be able to get the empirical data concerning emotion states and other internal states in large groups of persons. This would require extracting, each belief, intention and emotion of each person in a crowd, continuously. How would you do that? It seems impossible to extract these mental states continuously with some kind of helmet or machine attached to the persons. Perhaps asking the people to register what they feel and think all the time would be helpful, but will lead to interpretation of the persons themselves and perhaps will not be continuous. This is a general limitation in validation of computational models. Usually in practice it is only possible to acquire empirical data for some of the variables in a model, not for all.

A last limitation of the proposed models is the relatively large number of parameters. There is a trade-off in the amount of parameters; on the one hand, the proposed models are generic through their parameters, their values can be chosen and tuned to specific domains in a fine-grained manner. On the other hand, too many parameters would make the model less easy to handle, as all of them should get their value. It was always tried to keep the parameters to a minimum. The validation process of tuning the parameters in Chapter 6, could also be improved by using parts of the empirical data for the tuning process and different parts for the test of the model. In Chapter 6, the empirical data was not of enough length to use this validation approach, but a next time this approach is intended to be followed.

13.3 Future Work

Although the main research question was answered by addressing its more specific sub questions, still issues remain that require more work. In this section, future plans and new research questions are discussed. First, the emotion contagion models in Chapter 2 require more work in modelling multiple emotions at the same time and the interactions between different emotions. Also other representations of emotions should be explored, for example a multidimensional representation of an emotion, instead of the unimodal representation that was chosen (a number in the interval $[0, 1]$). A detailed validation of the model is planned as well. The plan is to create a setting in which various humans interact in a room, while continuously being subject to (physiological) measurements (e.g. using emotion recognition approaches as discussed in [8]) to assess their emotions. The obtained data can be used in order to fine-tune the model using adaptive and machine learning techniques. This will provide a more detailed validation of the model and results in realistic parameter settings for different types of individuals.

Chapter 3 did not give conclusive results and therefore asks for more experiments that investigate the effect of emotions on cognitive abilities. This can be conducted in the same way as is done in Chapter 3 and in different
domains. Besides thought action repertoires, creativity and memory, it would be interesting to investigate if emotions also have an effect on acquiring new skills or solving mathematical equations for example. This would test the broaden-and-build theory in new domains.

Future plans for the work in Chapter 4 exist of building the designed model into a mobile phone, so that the human’s voice can be analysed during conversations. This application would be useful to prevent people that have had a depression from a relapse. Furthermore, the proposed model can then learn from the person’s voice and is expected to become much more accurate.

The models addressed in Chapter 5, 6, and 7 are meant to be a stepping stone towards a support agent for persons that are evacuating. Now that the behaviour of an evacuating and panicked crowd have been modelled and validated, a supportive agent can be designed. Many smart devices are envisioned that can help the people to find their exit faster and to regulate the fear contagion in the crowd. For example, mobile phones and digital signs in public transport or in public spaces could communicate to each other and decide what information to give to which persons. The devices would have to be able to identify the emotions, beliefs and intentions in the persons and reason about these states to give appropriate instructions or advice to the persons. Also, it is planned to apply and validate ASCRIBE in more scenario’s.

The intelligent support agent proposed in Chapter 9 should be tested on informal caregivers. Does it really improve the physical and mental health of the informal caregivers? Do caregivers trust the system and do they like using it? Can the system be improved? Does it function better than non-artificial support, for example support by therapists? The model proposed in Chapter 10 can be used in many other agent-based models that would like to integrate emotion regulation and emotion contagion. Perhaps research into crowd behaviour would benefit from using it. Also, the work in Chapters 8 and 9 could be combined with the model in Chapter 10. This would make sense because it could be very important to consider how an informal caregiver of a depressed spouse uses his/her emotion regulation strategies to stay in a positive mood. This could mean that the domain model in Chapter 8 could be improved if it would be combined with emotion regulation mechanisms proposed in Chapter 10.

For the proposed model in Chapter 11, validation is also one of the planned tasks. It will be interesting to find out if the model can support team leaders in an appropriate manner and if different kind of team leaders would use the intelligent agent during their work. The next planned step for Chapter 12 is to design an agent-based model that can simulate the communications between different organisations during crisis management according to different approaches, e.g. a more net-centric approach. The outcomes of
different approaches would then be compared with the empirical trace of the Schiphol Airport Train Tunnel incident and can give an insight in which approach seems best in this scenario. Next, this agent-based model should also be applied to other crisis management scenario’s to find out if a certain management approach, like net centric crisis management, is always the best approach.

New research questions that come forth out of the current work are therefore of two kinds: (1) how to design, improve and validate agent-based models in other domains (2) how to design, improve and validate agent-based models that integrate internal and social processes plus cognitive and affective aspects in these new domains. Examples of other interesting new domains for designing intelligent support agents for teams are many. Amongst others are, stimulating young adults to exercise more by using their social networks, helping the elderly to live independent and staying healthy by monitoring their physical and mental health and by contacting their social relations for help, monitoring the group processes of a sports team during a competition and give advices to the coach on how to improve team performance. My prediction is that many of these intelligent support systems will be designed in the coming years, since more of these systems are requested by our community and because more and more devices can realise them.

References


Curriculum Vitae

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Natalie van der Wal was born on May 18, 1981 in Aalsmeer, the Netherlands. Natalie is a researcher and lecturer in Artificial Intelligence at VU University Amsterdam. She works in the Agent Systems Research Group that investigates methods and techniques for modelling and analysis of agent systems in the area of human-oriented Ambient Intelligence. She finished her dissertation entitled: “Social Agents: Agent-Based Modelling of Intergrated Internal Social Dynamics of Cognitive and Affective Processes” in 2012. She received her Masters degree (cum laude) in Artificial Intelligence in 2009, graduating on the topic of ‘Modelling Agent-Based Support Systems for Group Emotion and Group Development’. She also received a Bachelors Degree in Cognitive and Clinical Neuropsychology in 2007 and a Masters Degree in Media and Culture in 2003. Her research interests are modelling dynamics of agent systems in practical application areas, social diffusion of information and emotion, psychological disorders and treatments, eHealth and promoting a healthy lifestyle with the help of technology.
Nederlandse Samenvatting

Sociale Agenten
Agentgebaseerd Modelleren van Geïntegreerde Interne en Sociale Dynamica van Cognitieve en Affectieve Processen

Tegenwoordig worden mensen in verschillende domeinen ondersteund door technologie, denk bijvoorbeeld aan een slimme auto die de autobestuurder kan observeren. Dreigt de bestuurder in slaap te vallen of rijdt hij buiten zijn rijbaan, dan wordt hij gewaarschuwd. Andere voorbeelden zijn een vibrerende riem die een brandweerman naar de uitgang van een gebouw kan leiden wanneer er weinig zicht is, applicaties op smartphones die mensen hun leefstijl helpen te verbeteren, slimme medicijndoosjes die kunnen observeren wanneer de gebruiker een pil vergeet in te nemen en hem/haar waarschuwen, slimme woonomgevingen voor ouderen en zorg op afstand. Vraagstukken die nog open liggen binnen dit gebied zijn het ondersteunen van groepen of teams.

Hoe kan bijvoorbeeld een systeem worden ontworpen dat de gemoedstoestand van het sociale netwerk van een persoon met een klinische depressie in de gaten houdt en zorgt dat de mensen rondom de persoon met de depressie niet ook depressief raken? Hoe kan een slim systeem de fysieke en mentale toestand van de leden van een voetbalteam in de gaten houden tijdens een voetbalwedstrijd en adviezen aan de coach of spelers geven om blessures te vermijden? Hoe kunnen teams die problemen oplossen, aan het vergaderen zijn, stressvolle taken uitvoeren of in de ruimte werken ondersteund worden door technologie die hun lichamelijke en mentale toestanden kan meten, daarover kan redeneren en kan ingrijpen waar nodig?

Voor dit proefschrift zijn agentgebaseerde modellen ontwikkeld om teams te ondersteunen op het gebied van emotiebesmetting, besluitvorming, leiderschap en informatieverbreiding. Vragen die worden beantwoord zijn: hoe kunnen sociale interacties gemodelleerd worden en hoe kunnen deze sociale interacties worden ondersteund met agentgebaseerde computermodellen? Hoe kunnen interne toestanden (bijvoorbeeld intenties of geloofsovertuigingen over wat anderen denken en willen) worden geïntegreerd met de sociale interacties (bijvoorbeeld besluitvorming en informatieverbreiding) en hoe worden affectieve processen (bijvoorbeeld emotiebesmetting) geïntegreerd met cognitieve processen (bijvoorbeeld emotieregulatie) in agentgebaseerde computermodellen? Hoe kunnen al deze processen gezamenlijk worden ondersteund via een slim agentgebaseerd systeem? Simuleren de modellen de werkelijke processen correct? Zijn er andere modellen die de werkelijke processen nauwkeuriger modelleren?
De kracht van het huidige onderzoek ligt in de uitbreiding van de kennis over hoe innovatieve computermodellen, die interne en sociale menselijke processen integreren met affectieve en cognitieve processen, kunnen worden ontworpen en geanalyseerd. Enkele andere krachtige uitkomsten zijn: de ontwikkeling en validatie van het computermodel ASCRIBE, dat kan simuleren en voorspellen hoe paniek en informatie zich verspreidt binnen een evacuerende mensenmassa, de ontwikkeling van een systeem dat kan detecteren welke emotie verandert in de gebruiker aan de hand van het analyseren van zijn stem, een computermodel dat de verspreiding van een negatieve stemming en de emotieregulatie binnen een mens kan simuleren en een systeem dat kan observeren welk ontwikkelingsniveau en emotie een teamlid heeft/voelt en dat de teamleider kan adviseren welke handelingen uit te voeren om het teamlid zich zo efficiënt mogelijk te laten ontwikkelen en de groepssfeer op een goed peil houdt.

Vervolgonderzoek bestaat onder andere uit ondersteunende acties ontwerpen voor het model ASCRIBE en deze implementeren en testen op een grote groep mensen, het intelligente systeem dat mantelzorgers kan ondersteunen valideren en een agentgebaseerd model ontwerpen voor crisis management scenario’s en daarmee verschillende scenario’s simuleren en vergelijken met het Schiphol incident uit hoofdstuk 12. Nieuwe onderzoeksvragen die zijn voortgekomen uit dit onderzoek zijn: hoe kunnen agentgebaseerde systemen worden ontworpen in andere domeinen? Hoe kunnen interne en sociale processen geïntegreerd worden in deze nieuwe domeinen en een basis vormen voor de ondersteuning van de teamleden in hun taakuitvoering?
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# Appendices

## Appendix A  Settings for the Scenarios in Section 5.5

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## Appendix B  Settings for the Scenarios in Section 5.8

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### Scenario 3

| q (initial state) | Agent1 0.3 | 0.8 | 0.1 | 0.1 |
|                   | Agent2 0.9 | 0.1 | 0.1 | 0.1 |
|                   | Agent3 0.1 | 0.1 | 0.1 | 0.1 |
|                   | Agent4 0.1 | 0.1 | 0.1 | 0.1 |
| δ (openness)      | Agent1 0.2 | 1 | 0.1 | 0.1 |
|                   | Agent2 0.1 | 0.1 | 0.1 | 0.1 |
|                   | Agent3 0.7 | 0.5 | 0.5 | 0.5 |
|                   | Agent4 0.6 | 0.1 | 0.1 | 0.1 |
| η (amplify/absorb)| Agent1 0.5 | 0.9 | 0.9 | 0.9 |
|                   | Agent2 0.1 | 0.9 | 0.9 | 0.9 |
|                   | Agent3 0.2 | 0.1 | 0.1 | 0.1 |
|                   | Agent4 0.1 | 0.2 | 0.2 | 0.2 |
| β (bias)          | Agent1 0.1 | 0.9 | 0.1 | 0.1 |
|                   | Agent2 0.9 | 0.1 | 0.1 | 0.1 |
|                   | Agent3 0.5 | 0.5 | 0.5 | 0.5 |
|                   | Agent4 0.5 | 0.1 | 0.1 | 0.1 |